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SENSITIVITY ANALYSIS OF SUPERPAVE MIXTURE VOLUMETRIC PROPERTIES

Final Report

Prepared for

Kansas Department of Transportation

by

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16 **Abstract**

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Principal component analysis (PCA) and multiple correlation analysis (MCA) were conducted to identify the statistically significant variables and to develop quantitative relationships between the predictor and the response variables. The PCA indicates that the predictor variables can be selected from eight "subgroups" of correlated variables. Very good predictive equations were found using the predictors isolated in this study for the Va and VMA, but not for the in-place pavement density and TSR. Sensitivity analysis was performed to evaluate the effects of changes in the input variables on the response variables based on the predictive equations found in MCA.

Multiple property optimization (MPO) results show that the most desirable 19 mm nominal maximum size mixture would have Va close to 4%, VMA between 13% and 14%, dust proportion equal to 0.9%, and other factors in the ranges specified by KDOT Superpave mixture specifications.

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1.0 INTRODUCTION

1.1 Problem Statement

One of the final products of the Asphalt Research Program of the Strategic Highway Research Program (SHRP) is a new system called Superpave, short for Superior Performing Asphalt Pavements. Superpave represents an improved system for specifying asphalt binders and mineral aggregates, developing asphalt mixture design, and analyzing and establishing pavement performance prediction. It incorporates performance-based asphalt material characterization with the design environmental conditions to improve performance by controlling rutting, low temperature cracking and fatigue cracking *(McGennis et al. 1994)*. The Superpave binder specification and mix design system include various test equipment, test methods and criteria.

Superpave mix design and analysis is performed at one of three increasingly rigorous levels, depending upon design truck traffic volume, with higher levels providing more information about the mixture's performance capabilities than lower levels. Superpave volumetric mix design *(formerly known as Level 1)* is an improved material selection and volumetric mix design process. The volumetric mix design involves selecting asphalt and aggregate materials that meet the Superpave specifications, and then conducting a volumetric analysis of hot mix asphalt specimens compacted with a Superpave gyratory compactor.

The majority of routes on the state highway system in Kansas serve low traffic volumes. Therefore, most of the Superpave mix designs that are currently being used, as well as those that will be used in the future, are expected to fall under the Superpave volumetric mixture design category. Current Superpave volumetric mixture design requirements consist of *(McGennis et al. 1994)*:

a) mixture volumetric parameters,

b) dust proportion and degree of compactibility,

c) moisture sensitivity.

The Kansas Department of Transportation (KDOT) is actively pursuing a new Quality Control/Quality Assurance (QC/QA) program for the Superpave mixtures. For the purpose of pilot (change order) Superpave projects, the QC/QA program was developed by drawing upon historical hot mix asphalt project experience as well as guidelines of other agencies. It is, therefore, desirable to have detailed statistical analysis of the QC/QA test data obtained from the mixtures on the pilot projects and the projects that have been let and completed thus far, so that the QC/QA program can be improved.

1.2 Objective

This research focused on mixtures that were designed using the Superpave mix design system, and constructed on 12 recently built projects on the State, US and Interstate routes in Kansas. QC/QA data on mixture components and volumetric properties were collected from these projects.

The primary objective of this study was to investigate the effect of changes in the input variables on the response variables. The input variables were:

- asphalt binder content (Pb);
- percent of densification ($\%G_{mm}$) at $N_{maximum}$ and $N_{minimum}$;

- aggregate sizes (percent material retained on the 19 mm, 12.5 mm, 9.5 mm sieves and so on); and
- dust proportion (DP), sand equivalent (SE), fine aggregate angularity (FAA), and coarse aggregate angularity (CAA).

The response variables were:

- air voids at N_{design}(Va);
- voids in mineral aggregate (VMA);
- in-place pavement density, and
- moisture sensitivity in terms of tensile strength ratio (TSR).

1.3 Data Analysis Approach

To achieve the objective mentioned earlier, a four-step modeling approach was used:

***1. Principal Components Analysis (PCA)*:** PCA is a statistical technique used to screen out the less important predictor variables and retain the more important ones. In this study, data for all Superpave mixture parameters from all 12 projects was used in the PCA. PCA transforms a set of correlated variables into a smaller set of uncorrelated variables called principal components *(Johnson 1998)*. PCA results along with engineering judgement were used to group predictor variables into subgroups of similar type.

***2. Model Formulation and Calibration*:** After identifying the key predictor variables resulting from PCA, a series of linear relationships were formulated and calibrated using a multi-regression analysis software, MC *(MC 1991)*. Most recently, the MC software has been used in a pooled-fund study to identify the factors responsible for premature concrete pavement deterioration in the Federal Highway Administration (FHWA) Region 7 (Midwest) *(Jennings et al. 1997)*. In model formulation, the form of the model was developed on the basis of multiple correlation analysis results and engineering judgement. In model calibration, model constants were evaluated so that the best fit between the formulated model and the collected data was achieved.

*3. **Sensitivity Analysis***: After obtaining final correlation equations, a sensitivity analysis of the dependent variables was performed. The effects of changes in the input parameters on the response variables were plotted and discussed.

*4. **Multiple Property Optimization (MPO)***: At this point, the MPO is done for each type of mixture in the let projects. The final correlation equations for each type of mixture were used as input into a software called MPO *(MPO 1991)*, to determine how a process should be run in order to achieve an optimum combination of the independent variables which would result in Va, VMA, in-place pavement density, and TSR, as close to their target values as possible.

1.4 Synopsis

This report is divided into seven chapters. Chapter 1 is the introduction to the study. Chapter 2 is a literature review of the previous work. Chapter 3 describes the project selection and data collection. Chapter 4 describes the principal components analysis that was completed on 19 Superpave mixture parameters being monitored under the KDOT QC/QA program. PCA was used to partition 15 parameters (excluding four dependent variables) into subgroups so that the variables within a subgroup are highly correlated, but there is no significant correlation of variables between the subgroups. One variable from each subgroup was selected as an independent variable in the multiple correlation analysis. Chapter 5 describes a multiple correlation analysis that was performed to obtain the relationships between dependent variables (Va, VMA, in-place pavement density, and TSR) and the independent variables obtained from PCA results for each type of mixture. Sensitivity analysis performed for each equation is also presented. Chapter 6 presents the methodologies of multiple properties optimization, and its application in this study to obtain the optimum combination of the independent variables. This analysis resulted in Va and VMA being as close to their respective targets as possible. Finally, Chapter 7 summarizes the conclusions and recommendations of this study.

2.0 LITERATURE REVIEW

Asphalt concrete pavement covers more than 90% of the paved roads in the United States *(Huang 1993)*. Before the introduction of the Superpave mix design system, asphalt mixtures were typically designed using empirical laboratory design procedures, and field experience was necessary to determine if the laboratory analysis correlated with the pavement performance *(The Asphalt Institute 1995)*. During the past 20 years or so, asphalt pavement life has been significantly shortened by increased traffic, heavier trucks, and higher-pressure tires, even with proper adherence to the specified mix design criteria and procedures. In 1987, the Strategic Highway Research Program (SHRP) initiated a study to develop a new system for specifying asphalt materials. The final product of this SHRP asphalt research is a new system called Superpave, short for <u>Su</u>perior <u>Per</u>forming Asphalt <u>Pave</u>ments *(The Asphalt Institute 1995)*.

The resulting Superpave system gives highway engineers and contractors a new set of tools for designing asphalt pavements that will perform better at extreme temperatures and under heavy loads *(Lucas 1997)*. The Superpave system predominately addresses three principal types of pavement distress to be considered for flexible pavement design: rutting (permanent deformation or rut depth along the wheelpath), which is caused by inadequate shear strength in the asphalt mix; fatigue cracking, which results from the tensile strain in the asphalt layer due to repeated loads; and low-temperature cracking, which results when the thermal stress in the pavement due to a low-temperature event exceeds the fracture strength of the asphalt concrete *(Huang 1993)*. The system is built around three major components: an asphalt binder specification, a volumetric mix design and analysis system, and a performance prediction system *(The Asphalt Institute 1995)*.

A primary objective of the state highway agencies (SHAs) and contractors is to achieve a quality hot-mix asphalt (HMA) pavement. Over the past several years, interest in the Superpave performance-based mix design and analysis is rapidly growing throughout the nation. SHAs have been working with the construction industry to implement quality control/quality assurance (QC/QA) specifications to improve the quality of HMA construction. Movement away from method-based specifications toward QC/QA specifications and warranty specifications has decreased agency involvement in design and construction phases of a project *(Schmitt et al. 1998)*. The American Association of State Highway and Transportation Officials (AASHTO) developed the *Implementation Manual for Quality Assurance* to provide agencies with the structure and guidelines for implementing a Quality Assurance (QA) program *(AASHTO 1994a)*. Determining the extent of variation in the materials and testing is an important element within the specification. Pay factors are suggested to be set to encourage quality and be related to the expected loss or gain in service life of the product. Incentive payments should be granted to the contractors for achieving proper control of the construction process and expected increase in pavement life. AASHTO *Quality Assurance Guide Specification (AASHTO 1994b)* provided definitions, methods, and procedures for assuring highway construction quality. Once a commitment has been made to implement a QA program, this AASHTO guide provides detailed specifications for assuring highway construction quality using statistics and other quantitative methods.

Frequencies for contractor testing and inspection are set as needed to control operations, while agencies determine their own individual testing and inspection frequencies. Methods for testing and evaluating mixture properties and in-place pavement density are provided, and tolerances have been established for the mixture properties which include aggregate gradation and asphalt binder content. The tolerances are applied to the pertinent mix design variable values from the Job Mix Formula (JMF).

2.1 Superpave Mixture Design Specifications

The Superpave mix shall be designed with the Superpave mix design method to obtain a Laboratory Trial Mix Formula (LTMF) based on the following criteria: *(Cominsky et al. 1998)*

***Control points and restricted zone*:** The Superpave mix design resulting in the LTMF shall provide for the selection of aggregate gradation for the paving mix by means of control points and a restricted zone. The control points and restricted zone are plotted on the FHWA's grading chart on which the percent of aggregate passing a sieve size is plotted against the sieve opening size raised to the 0.45 power. Table 2.1 identifies the control points for gradations with nominal maximum sizes of 19.0, 12.5, and 9.5 mm, respectively.

***Coarse aggregate angularity (CAA)*:** The LTMF shall be based on the design traffic levels associated with the coarse aggregate angularity with the values shown in Table 2.2 being the minimum.

***Fine aggregate angularity (FAA)*:** The LTMF shall be based on a design traffic level associated with the fine angularity with the value shown in Table 2.3 being the minimum.

Dust proportion (DP): The dust proportion or dust-to-effective asphalt ratio shall be between 0.6 and 1.2 for all design traffic levels.

Air voids (Va): The design air voids for the LTMF shall be 4% for all traffic levels.

Voids in mineral aggregate (VMA): The acceptable values for VMA for the LTMF at 4% air voids, based on the nominal maximum size aggregate, are shown in Table 2.4.

Gyratory compaction: The number of initial ($N_{initial}$), design (N_{design}), and maximum ($N_{maximum}$) gyrations shall be based on the design traffic level and the average design high air temperature. Density shall be evaluated as a percent of the maximum theoretical specific gravity of the loose mixture at the initial number of gyrations ($N_{initial}$), the design number of gyrations (N_{design}), and the maximum number of gyrations ($N_{maximum}$).

Compaction requirements: The gyratory-compacted specimens for the LTMF shall meet the density requirements specified in Table 2.5.

Moisture sensitivity: The compacted specimens of the LTMF shall exhibit a minimum tensile strength ratio (TSR) of 80 percent as determined by AASHTO T283.

2.2 QC/QA Specifications

Schmitt et al. (1998) conducted a study on the QC/QA specifications which are in use in 40 states. Many of the specifications are dated 1996 and are either initial drafts or revisions. The information from these specifications was divided into two categories: acceptance testing, including mixture properties and in-place pavement density, and pay adjustments.

Table 2.1 Superpave Aggregate Gradation Control Points

(a) 19.0 mm Nominal Maximum Size

Sieve Size	Control Point (Percent Retaining)	
	Maximum	Minimum
0.075 mm	98	92
2.36 mm	77	51
12.5 mm	--	10
Nominal Maximum (19.0 mm)	10	0
Maximum (25.0 mm)	0	--

(b) 12.5 mm Nominal Maximum Size

Sieve Size	Control Point (Percent Retaining)	
	Maximum	Minimum
0.075 mm	98	90
2.36 mm	72	42
9.5 mm	--	10
Nominal Maximum (12.5 mm)	10	0
Maximum (19.0 mm)	0	--

(c) 9.5 mm Nominal Maximum Size

Sieve Size	Control Point (Percent Retaining)	
	Maximum	Minimum
0.075 mm	98	90
2.36 mm	68	33
4.75 mm	--	10
Nominal Maximum (9.5 mm)	10	0
Maximum (12.5 mm)	0	–

Table 2.2 **Superpave Coarse Aggregate Angularity Requirements**

Traffic(ESALs)	**Depth from Surface**	
	<100 mm	**>100 mm**
$< 3 * 10^5$	55/--	--/--
$< 1 * 10^6$	65/--	--/--
$< 3 * 10^6$	75/--	50/--
$< 1 * 10^7$	85-80	60/--
$< 3 * 10^7$	95/90	80/75
$< 1 * 10^8$	100/100	95/90
$> 1 * 10^8$	100/100	100/100

Table 2.3 **Superpave Fine Aggregate Angularity Requirements**

Traffic(ESALs)	**Depth from Surface**	
	<100 mm	**>100 mm**
$< 3 * 10^5$	--	--
$< 1 * 10^6$	40	--
$< 3 * 10^6$	40	40
$< 3 * 10^7$	45	40
$< 1 * 10^8$	45	45
$> 1 * 10^8$	45	45

Table 2.4 Superpave VMA Requirements

Nominal Maximum size	Minimum Voids in Mineral Aggregate (%)
9.5 mm	15.0
12.5 mm	14.0
19.0 mm	13.0

Table 2.5 Superpave Compaction Requirements

Compaction Level	Required Density
$N_{initial}$	< 89.0% of G_{mm}
N_{design}	= 96.0% of G_{mm}
$N_{maximum}$	< 98.0% of G_{mm}

A review of the specifications consistently found three fundamental measures for acceptance testing: mix properties, in-place pavement density, and smoothness. These measures described overall pavement quality by measuring the HMA material composition (mixture properties), the densification of the material to withstand repetitive loads from traffic (in-place pavement density), and the ride quality experienced by the traveling public (smoothness). Whether viewed independently or collectively, these measures typically describe the quality level achieved during construction.

Five different statistical measures were found to be used to determine specification compliance: average, average absolute deviation, moving average, range, and quality level analysis. Table 2.6 tabulates the characteristics of these compliance measures along with supporting equations. Each of these measures has unique statistical characteristics, and how variation is managed by each method must be given careful consideration when determining testing levels and product acceptance in the QC/QA specifications.

2.2.1 Mix Properties

The survey found that there were three primary groups of variables for evaluating mixture properties: (1) aggregate gradation; (2) asphalt binder content; and (3) mixture volumetrics (air voids, voids in mineral aggregate, and so forth). A majority of states were using tonnage to define sublot and lot sizes. Sublot sizes range from one test per 454 tonnes (500 tons) to as high as one test per 1,814 tonnes (2,000 tons). Asphalt binder content was evaluated more than aggregate gradation and mix volumetrics for both sublots and lots. KDOT and its contractors are using the ignition oven to determine the asphalt binder content and aggregate gradation because it is faster and more precise than other methods.

Quality level analysis is the most frequently specified compliance measure for the three primary mix properties. Absolute average deviation followed closely by moving average are the next most common methods for measuring specification compliance.

2.2.2 In-place Pavement Density

A large number of states are using tonnage for sublots and lots similar to the plant-produced mixtures. Sublot sizes ranged from one test per 73 tonnes (80 tons) to one test per 1,361 tonnes (1,500 tons). Other specified sublot and lot sizes were length, time, and area. Time for sublots and lots ranged from one to five per day. Five per day is used by KDOT for in-place pavement density measurements.

Table 2.6 Description of Compliance Measures

Compliance Measure (1)	Characteristics (2)	Equation (3)
Average	• Arithmetic average of tests • Variation must be known since it determines how accurately the average can be estimated from a given sample size. • A confidence interval should be constructed to describe the interval of the mean that can be found at a specified probability level.	$\text{C. I.} = z_{\alpha/2} \sqrt{\frac{\sigma^2}{n}}$ where C.I. = Confidence Interval of mean; $z_{\alpha/2}$ = standardized statistic; σ^2 = known variance; and n = number of tests.
Quality Level Analysis	• Estimates Percent Within Limits (PWL) using the sample mean and standard deviation. • Using the interrelationship of the mean and standard deviation to estimate PWL develops a distribution of the process. • Quality indices for the upper (Q_U) and lower (Q_L) specification limits are first calculated, then applied to statistical tables to determine the estimated PWL.	$Q_U = \frac{(USL - \bar{X})}{s}$ $Q_L = \frac{(\bar{X} - LSL)}{s}$ where USL = Upper Specification Limit; LSL = Lower Specification Limit; $\bar{X}$ = sample mean; and s = sample standard deviation.
Absolute Average Deviation	• Average of absolute deviations from a target value, typically the JMF design value. • Specifications are currently structured to allow greater cumulative deviations from the target for smaller sample sizes.	$\Delta = \frac{(\Sigma \lvert X - TV \rvert)}{n}$ where Δ = average absolute deviation; X = individual test result; TV = Target value; and n = number of tests.
Moving Average	• Measures the arithmetic moving average of several consecutive tests. • Evaluates changes or trends in the moving average relative to target values or specification limits.	$\bar{X} = \frac{(\Sigma X)}{n}$ where $\bar{X}$ = sample mean; X = individual test result; and n = number of tests.
Range	• Measures the arithmetic range of tests. • Compares the range of values to specification limits, but does not compute the distribution of this range.	Range = (Max – Min) where Max = Maximum test value; and Min = Minimum test value.

Methods to sample pavement density include core samples, nuclear density readings, and correcting the nuclear density readings to the core densities, with the number of correction tests ranging from 3 to 12. ASTM D2950-91, "Standard Test Method for Density of Bituminous Concrete in Place by Nuclear Methods," recommends that at least seven core densities and seven nuclear densities be used to establish a conversion factor *(ASTM 1992)*. It is recommended that a new conversion factor be established any time a change was made in the paving mixture or in the construction process. In-place pavement density was referenced by several procedures, including theoretical maximum density (TMD), laboratory maximum density (LMD), test strip, and roadway voids. It is expected that more states would use TMD because Superpave testing protocols use this in mix volumetric analysis. Similar to the plant-produced mixture properties, quality level analysis was the most common compliance measure for density (20 states). The average method was next most common (eight states), followed by range (four states), absolute average deviation (three states), and moving average (three states).

2.2.3 Pay Adjustments

Pay adjustments have become an integral part of nearly every QC/QA specifications. The survey found that 95 percent of the states have some type of pay adjustment applied to the level of quality measured by the test results *(Schmitt et al. 1998)*. In theory, pay adjustment is the difference between the planned life-cycle costs from the design and expected life-cycle costs from the as-built construction quality.

There are many attributes to be considered when making pay adjustments. Pay adjustments have been developed for plant-produced mixture properties (aggregate gradation, asphalt binder content, and mixture volumetrics) and construction tests (in-place pavement density and smoothness).

There were two primary methods for selecting a pay adjustment: a factor (or multiplier) and a fixed rate. The factor method was the most common, and it applied a predetermined pay percentage to the measured test results, usually in the form of a pay table. Other states used a fixed rate adjustment that varied with the measured quality level but did not use a percentage to adjust payment.

The most common aggregate sieve size used for pay adjustment was 0.075 mm. The next most commonly specified sieve sizes were 4.75 and 2.36 mm, where these sieves defined the particle size between the coarse and the fine aggregates. Many states specified both sieve sizes in their specifications. Percent of TMD was used primarily for payment of in-place pavement density, agreeing with an earlier finding in the specifications where most states used TMD as a density reference value.

A majority of the states were using weighted values to determine the pay factor for a lot, where weights that sum to 1.0 are multiplied by individual pay components, and then added. However, there was variation in the coefficients assigned and no consensus regarding the individual equation components. AASHTO refers to these weighted-type pay adjustments as "composite pay factors" *(AASHTO 1994b)*.

2.3 KDOT Quality Control/Quality Assurance (QC/QA) Program

KDOT is considering full implementation of the Superpave mixture design by the year 2000.

As Superpave itself is a performance-based system, the QC/QA program of KDOT will be developed as part of the statistical performance-based specifications. KDOT has drafted additional requirements for Superpave mixtures, which are partially in the form of performance-based specifications. These along with existing KDOT Standard Specifications were adopted as the specifications for the Superpave projects in Kansas.

KDOT specifications include quality control (QC) tests to ensure conformance of up to 19 important aggregate and Superpave mixture parameters. Because of the interrelationships among some parameters, continual control of all mix properties may not be necessary. Out of 19 parameters, KDOT has specified working ranges (limits) to monitor the 11 mixture parameters shown in Table 2.7 along with the compacted pavement density (in-place pavement density) under quality control operations using control charts *(Hossain et al. 1997)*. The specification working ranges shown in Table 2.7 have been set by KDOT based on historical experience and engineering judgement and refer to the mixture design requirements in Table 2.8. Bonus or deduct payments in the specifications are based on the air void percentage and in-place pavement density only *(Hossain et al. 1997)*. For specification limits, KDOT uses single point test values for five parameters and applies additional dual criteria of four-point moving averages for the other parameters. If two consecutive single point test results or any one four-point moving average value fails to fall within the respective established limits, KDOT will require suspension of mixture production until appropriate corrective measures are adopted *(Hossain et al. 1997)*.

Table 2.7 Specification Working Ranges (QC/QA) of the Kansas Superpave Mixtures

Mix Characteristic	**Tolerance from JMF Single Test Value**	**Tolerance from JMF (4 Point Moving Average Value)**
Binder Content (Pb)	+/- 0.6%	+/- 0.3%
Mix Characteristic	Tolerance from Specification Limits Single Test Value	Tolerance from Specification Limits - 4 Point Moving
Gradation :-		
All applicable sieves	NA	zero tolerance
Air Voids (Va)	+/- 2.0 %	NA
Voids in Mineral Agg. (VMA)	1.0% below min.	zero tolerance
Voids Filled with Asphalt (VFA)	NA	zero tolerance
Coarse Agg. Angularity (CAA)	zero tolerance	NA
Sand Equivalent (SE)	zero tolerance	NA
Fine Agg. Uncompacted Voids (FAA)	zero tolerance	NA
Tensile Strength Ratio (TSR)	zero tolerance	NA
Density (%G_{mm}) at N_{ini} and N_{max}	NA	zero tolerance
Dust/Binder Ratio (DP)	NA	zero tolerance

Table 2.8 Superpave Mix Design Requirements

Mix Design.	25 mm	19 mm	12.5 mm	9.5 mm	4.75 mm	2.36 mm	1.18 mm	0.600 mm	0.300 mm	0.075 mm	Min. VMA%
9.5 mm			0	0-10	10 min	53 - 68	68 min	76 min	81 min	90 - 98	15
12.5 mm (coarse)		0	0-10	10 min		61 - 72	74 min	81 min	84 min	90 - 98	14
12.5 mm (coarse, modified)		0	0-10	10 min		61 - 72	74 min	81 min	84 min	90 - 98	14
12.5 mm (fine)		0	0-10	10 min		42 - 61	68 max	77 max	84 max	90 - 98	14
12.5 mm (fine, recycled)		0	0-10	10 min		42 - 61	68 max	77 max	84 max	90 - 98	14
12.5 mm (fine, modified)		0	0-10	10 min		42 - 61	68 max	77 max	84 max	90 - 98	14
12.5 mm (modified, recycled)		0	0-10	10 min		42 - 61	68 max	77 max	84 max	90 - 98	14
19.0 mm (coarse)	0	0-10	10 min	10 min		65 -77	78	83 min	86 min	92 - 98	13
19.0 mm (coarse, recycled)	0	0-10	10 min	10 min		65 -77	78	83 min	86 min	92 - 98	13

* recycled mix

1. The requirements for coarse aggregate angularity; uncompacted voids content of fine aggregates; sand equivalent; Superpave gyratory compaction revolutions N_{ini}, N_{des}, N_{max}; and void filled with asphalt will be as shown in the contract special provisions for each mix designation.
2. The flat or elongated particles in the coarse aggregate must not exceed 10 percent.
3. The maximum percent moisture in the final mixture must not exceed 0.5 for any max designation.
4. The dust to binder ratio D/B shall be within the range of 0.6 to 1.2 for any mix designation.
5. The target air voids for any mix designation is 4.0 % at N_{des} gyrations.
6. The minimum tensile strength ratio is 80 % for any mix designation.
7. The level of compaction of the mix when compacted to N_{ini} gyrations is less than 89 percent of the maximum specific gravity and when compacted to N_{max} gyrations is less than 98 percent of the maximum specific gravity.

KDOT has collected data from the plant-produced Superpave mixtures over the last three construction seasons. This study was initiated to understand the significance of different parameters monitored in the QC/QA program for four output parameters, namely air voids at N_{design}, voids in mineral aggregates, in-place pavement density, and moisture sensitivity.

2.4 Sensitivity of Superpave Mixture Tests to Changes in Mixture Components

2.4.1 NCHRP Project 9-7

Cominsky et al. *(1998)* conducted a study titled " Sensitivity of Superpave Mixture Tests to Changes in Mixture Components" as part of the National Cooperative Highway Research Program (NCHRP) project 9-7 "Field Procedures and Equipment to Implement SHRP Asphalt Specifications." The research focused on mixtures that were designed and constructed using the Superpave mix design system on 11 projects in Kentucky, Mississippi, Virginia, Florida, Texas, Kansas, Maryland, and Alabama. The purpose of the research was to analyze whether laboratory changes in mixture components will result in significant mixture property (volumetric and mechanical) changes.

The experiment was designed to investigate changes in the following input variables:

- asphalt binder content;
- change in coarse aggregate gradation (material retained on the 4.75 mm sieve);
- change in intermediate aggregate gradation (material passing the 4.75 mm sieve and retained on the 0.3 mm sieve);
- change in fine aggregate gradation (material passing the 0.3 mm sieve);

• change in ratio of natural and crushed sands.

The effects of changes in the input variables on the following response variables were investigated:

• percent of densification ($\%G_{mm}$) or air voids, at N_{design};

• percent of densification ($\%G_{mm}$) at $N_{initial}$ and $N_{maximum}$;

• densification slope ($\%G_{mm}$ as a function of number of gyrations).

2.4.2 Experimental Design

The experiment was designed as a quarter factorial of a 2^5 design; a $2_{III}{}^{5}$ fractional factorial with a center point (control). A full factorial 2^5 design would have required a total of 256 compacted specimens (32 cells, plus one center point, with a minimum of eight compacted specimens per cell). The $2_{III}{}^{5-2}$ fractional factorial design reduced the number of compacted specimens to 72. Table 2.9 indicates the experimental design. Table 2.10 describes the experimental design with alias structure. If all third-order and higher interactions are considered negligible, then the $2_{III}{}^{5-2}$ experimental design provides data on main effects aliased with second-order interactions involving variable A (asphalt content).

Table 2.9 Experimental Matrix

		A_0				A_1			
		B_0		B_1		B_0		B_1	
		C_0	C_1	C_0	C_1	C_0	C_1	C_0	C_1
D_0	E_0				B8	B3			
	E_1			B4			B7		
D_1	E_0		B6					B5	
	E_1	B2							B9

Where: A_0 is the low level of variable A, B_1 is the high level of variable B, etc. B3 is Blend 3, etc.

Variable A is asphalt binder content.
Variable B is fine aggregate gradation.
Variable C is coarse aggregate gradation.
Variable D is intermediate aggregate gradation.
Variable E is ratio of natural and crushed sands.

Table 2.10 Experimental Design and Alias Structure

Variable							
A	B	C	D=AB	E=AC	Treatment	Blend	Effect
L	L	L	H	H	(1) (de)	2	-
H	L	L	L	L	a	3	l_A = A+BD+CE+ABCDE
L	H	L	L	H	b (e)	4	l_B = B+AD+CDE+ABCE
H	H	L	H	L	ab (d)	5	l_{AB} = AB+D+BCE+ACDE
L	L	H	H	L	c (d)	6	l_C = C+AE+BDE+ABCD
H	L	H	L	H	ac (e)	7	l_{AC} = AC+E+BCD+ABDE
L	H	H	L	L	bc	8	l_{BC} = BC+DE+ACD+ABE
H	H	H	H	H	abc (de)	9	l_{ABC} = BE+CD+ABC+ADE

The alias structure is determined from the defining relation I = ABD = ACE = BCDE:

A = BD = CE = ABCDE
B = AD = ABCE = CDE
C = ABCD = AE = BDE
D = AB = ACDE = BCE
E = ABDE = AC = BCD
BC = ACD = ABE = DE
BE = ADE = ABC = CD

2.4.3 *Some Conclusions*

The conclusions of this study pertain to the specific combination of materials used in the experiment. It was initially thought that different aggregates and gradations would have different sensitivities to changes in material components. For instance, a 9.5 mm gravel mixture may have a different sensitivity to changes in intermediate gradation than the study mixture.

In all cases, the blend with higher asphalt content resulted in higher percent G_{mm} at N_{design} and lower air voids. The differences between the complementary pairs were consistent with the expectations from the Superpave mixture design equations. Superpave equations relate one percent change in asphalt content to two and one-half percent change in air voids.

Initial analysis of percent G_{mm} at N_{design} indicated that the main effects of asphalt content, fine gradation, and coarse gradation, as well as the interaction of asphalt content and fine gradation, had significant effects on the percent G_{mm} at N_{design} (percent of air voids).

The main effects of intermediate gradation and ratio of natural and crushed sand appeared to have an insignificant effect on the percent G_{mm} at N_{design} (percent of air voids). However, comparison of identical blends (ignoring the intermediate gradation and ratio of natural and crushed sand as variables) indicated a difference in air voids of three to six percent. These differences indicated that either the intermediate gradation and ratio of natural and crushed sand had an effect on the percent G_{mm} at N_{design} (percent of air voids), although not as significant as other variables, or the third-order interactions aliased with these variables had an effect.

The analysis of percent G_{mm} at $N_{initial}$ indicated the following significant effects: the interaction of asphalt content and fine gradation aliased with the fourth-order interaction of asphalt content, coarse gradation, intermediate gradation, and ratio of natural and crushed sand; coarse gradation aliased with the third-order interaction of fine gradation, intermediate gradation, ratio of natural and crushed sand; asphalt content aliased with the fifth-order interaction of all five variables; the interaction of asphalt content and coarse gradation aliased with the fourth-order interaction of asphalt content, fine gradation, intermediate gradation, and ratio of natural and crushed sand; and fine gradation aliased with the third-order interaction of coarse gradation, intermediate gradation, and ratio of natural and crushed sand.

The analysis of percent G_{mm} at $N_{maximum}$ indicated the following significant effects: the interaction of asphalt content and fine gradation aliased with the fourth-order interaction of asphalt content, coarse gradation, intermediate gradation, and ratio of natural and crushed sand; fine gradation aliased with the third-order interaction of coarse gradation, intermediate gradation, ratio of natural and crushed sand; asphalt content aliased with the fifth-order interaction of all five variables; and coarse gradation aliased with the third-order interaction of fine gradation, intermediate gradation, and ratio of natural and crushed sand.

The interaction of asphalt content and fine gradation appeared to have the most significant effect on all volumetric and densification properties. Blends with high levels of asphalt content and fine gradation had higher densification (percent G_{mm} at $N_{initial}$, N_{design}, and $N_{maximum}$) and lower air voids than blends with low levels of asphalt content and fine gradation.

2.4.4 *Some Comments*

Although some meaningful conclusions have been drawn from this research, the conclusions are only based on laboratory-mixed materials. Also, there are other mixture properties, in addition to the variables used in this study, that are known to affect the volumetric properties of the mixtures. Examples are the sand equivalent, fine aggregate angularity, coarse aggregate angularity, and dust proportion. Also, the relationships investigated in the NCHRP 9-7 study were qualitative. A series of quantitative relationships would be a valuable tool for engineers to make decisions on the working ranges of the mixture parameters from existing data on the plant-produced Superpave mixtures *(Chen et al. 1999)*.

3.0 PROJECT SELECTION AND DATA COLLECTION

3.1 Project Selection

The projects for this research were subdivided based on the contract type (change order or let). Some of the Superpave projects in Kansas were designated as pilot projects (change order) in KDOT's QC/QA program. In change order projects, the QC/QA program was designed by drawing upon historical hot mix asphalt project experience as well as by using guidelines of other agencies. These projects were negotiated to be built as Superpave pavements under a change order. The other projects had been let and completed under specifications set by KDOT's QC/QA program *(Hossain et al. 1997)*. In total, 12 recently-built Superpave projects in Kansas were selected in this study. Table 3.1 lists the locations and mixture types of the projects in this study. A pavement section was defined as a pavement constructed by one contractor with a specific asphalt binder content and

aggregate mixture design. The sections varied in lengths from about 6 km to 24 km on the State, US and Interstate routes in Kansas. The geographical locations of these projects are shown on the Kansas map in Figure 3.1. Almost all projects are located in central and northeast Kansas, except two, Sections 8 and 9, on US-83, are in northwest Kansas.

Table 3.1 List of Superpave Projects in this Study

Section	Projects Number	Route	County	Length (km)	Mixture Type	Contract Type	Contractor
1	254-08-K5060-02	K-254*	Butler	7.66	SM-2C SM-1T	Let	Shears
2	254-87-K5058-02	K-254*	Sedgwick	8.96	SM-2C SM-1T	Let	Shears
3	24-75-K3325-02	US-24	Riley	14.64	SM-1T SM-2A	Change Order	Shilling
4	177-81-K3245-02	K-177	Riley	12.66	SR-2C SM-1T SM-2C	Change Order	Shilling
5	75-70-K4690-02	US-75	Osage	9.04	SM-2C	Let	Hamm
6	70-27-K5982-01	I-70	Ellsworth	23.27	SR-2C	Let	US Asphalt
7	70-85-K2610-01	I-70	Saline	12.84	SR-2C SM-2C	Change Order	Venture
8	83-55-K5388-01	US-83	Logan	24.01	SM-2C	Let	Ritchie
9	83-20-K6480-01	US-83	Decatur	20.00	SM-2A	Change Order	Allied
10	281-76-K5390-01	US-281	Pratt	11.07	SM-2C	Let	Venture
11	96-87-K4459-01	K-96	Sedgwick	6.24	SM-1T	Change Order	Ritchie
12	96-78-K4458-01	K-96	Reno	6.70	SM-1T	Change Order	Ritchie

* these projects are on the same stretch of the highway K-254 but were let separately

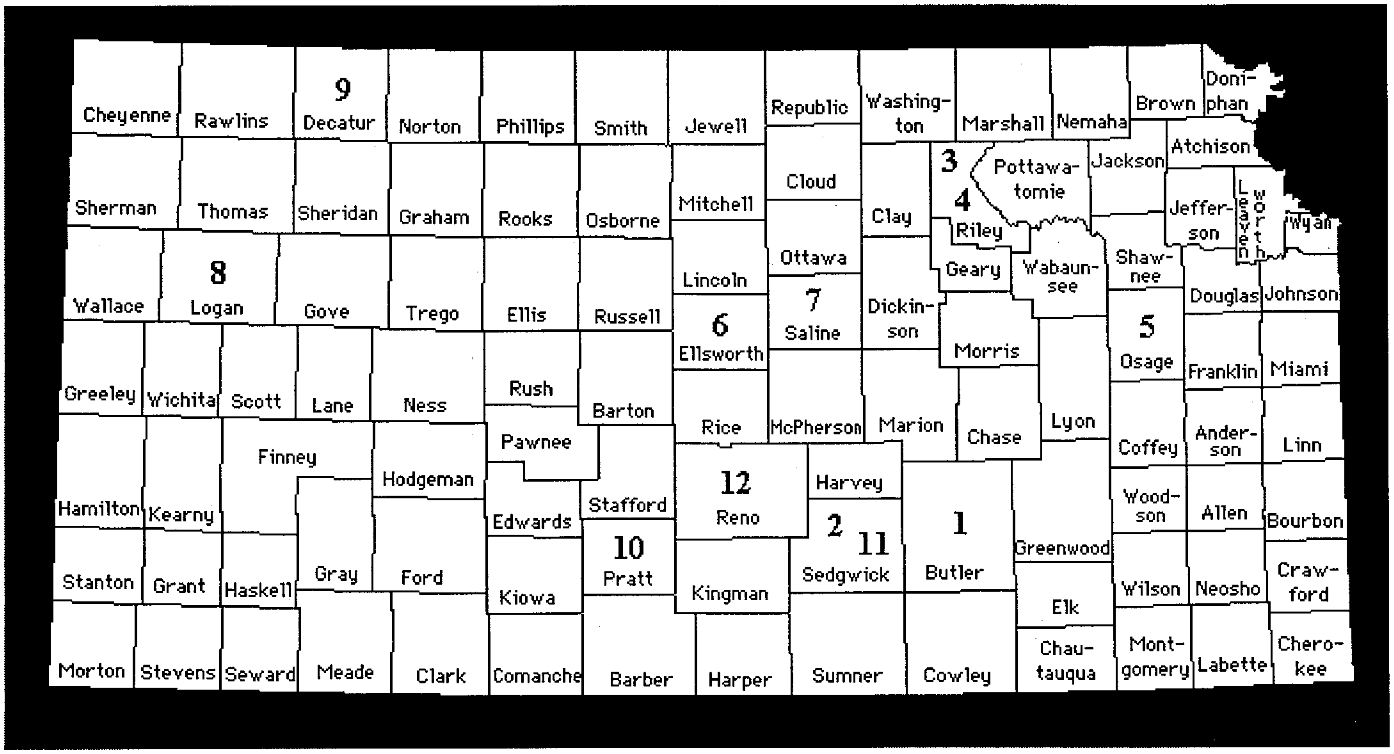

Figure 3.1 Geographical Locations of Selected Projects in Kansas Map

3.2 Data Collection

Data collection was one of the major tasks in this study, and this data served as the foundation for all results obtained by the statistical analysis. However, numerous obstacles, such as, lack of complete and properly maintained records, made this task difficult.

As mentioned earlier, KDOT currently monitors up to 19 mix parameters for Superpave mixtures under its QC/QA testing program. The test results generated in the QC/QA program over last three construction seasons were collected either directly from the contractors or from the responsible KDOT offices. All data was entered into a Microsoft Excel spreadsheet, and for each spreadsheet, 19 mix parameters were listed in columns and lot and sublot numbers were listed in rows. Some of these parameter were selected as independent variables (input variables) and some as dependent variables (response variables) as shown in Table 3.2. Table 3.3 shows the availability of the mix parameter data for each project. The "X" mark in each cell means that the data of the parameter (column) is available for the project (row), and a blank indicates missing data.

One problem encountered here was matching the Va and VMA data with the in-place pavement density data because the lot and sublot sizes of Va and VMA are based on a different system than in-place pavement density. KDOT has defined a standard mixture production lot size on a tonnage basis as 2,721 tonnes (3,000 tons). The sample size specified is four, resulting in four sublots of 680 tonnes (750 tons) in each lot for VA and VMA. However, for the in-place pavement density determination, lot size is defined on a time basis as one day's production. This is subject to a minimum of 1,000 tons daily production (quantitative basis). Each lot is divided into five sublots with two tests per sublot

Table 3.2 List of Selected Dependent and Independent Variables

Dependent Variables	Independent Variables
Air Void (%)	Asphalt Binder Content (%)
VMA (%)	$\%G_{mm}$ @ $N_{maximum}$
In-place Pavement Density (%)	$\%G_{mm}$ @ $N_{initial}$
Moisture Sensitivity (TSR) (%)	% Retained on 19 mm sieve
	% Retained on 12.5 mm sieve
	% Retained on 9.5 mm sieve
	% Retained on 2.36 mm sieve
	% Retained on 1.18 mm sieve
	% Retained on 0.6 m sieve
	% Retained on 0.3 m sieve
	% Retained on 0.075 m sieve
	Sand Equivalent (%)
	Fine Aggregate Angularity (%)
	Coarse Aggregate Angularity (%)
	Dust Proportion

Table 3.3 Data Availability for Each Project

Section	% Air Void	VMA	Density in place	TSR	Binder Content	%Gmm (Nmax)	%Gmm (Nmin)	%Retain 19 mm	%Retain 12.5 mm	%Retain 9.5 mm	%Retain 2.36 mm	%Retain 1.18 mm	%Retain 0.6mm	%Retain 0.3 mm	%Retain 0.075 mm	Sand Equiv.	FAA	CAA	Dust Prop
1	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X		X
2	X	X			X	X	X	X	X	X	X	X	X	X	X	X	X		X
3	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X
4	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X
5	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
8	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
9	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
10	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
11	X	X	X		X	X	X									X			
12	X	X	X		X	X	X									X			

(Hossain et al. 1997). Due to the fact that the date of each Va and VMA test is available for all projects, it was decided that in-place pavement density data would match the Va and VMA data on a time basis. The average value of each day (lot size of in-place pavement density) was used as the sublot value on a tonnage basis for Va and VMA, because the in-place pavement density tests were conducted at random spots.

4.0 PRINCIPAL COMPONENTS ANALYSIS

4.1 Background

Principal components analysis (PCA) is a statistical technique used in data reduction or in detecting the principal constructs of a system *(Johnson 1998)*. When a moderate to large number of predictor variables (say 15 to 40) are gathered to predict some dependent variables, PCA may be used to screen out the less important predictor variables and retain the more important ones. PCA is also used to detect structure in the relationships between variables, that is, to classify variables (*Stevens 1986)*.

PCA is a mathematical procedure that transforms a set of correlated variables into a smaller set of uncorrelated variables called principal components. The technique is useful in understanding the dependencies among variables of a set and also in determining whether subsets of variables cluster, or go with one another. Analyses of principal components are more of a means to an end rather than an end in themselves, because they frequently serve as intermediate steps in much larger investigations. For example, principal components may be inputs to a multiple regression or cluster analysis *(Johnson 1998; Stevens 1986)*.

The basic idea of PCA can be explained as follows: assume that two variables are linearly correlated. A regression line can then be fitted that represents the "best" summary of the linear relationship between the variables. If a variable can be defined that would approximate the regression line in such a plot, then that variable would capture most of the "essence" of the two items. Single scores on that new factor, represented by the regression line, could then be used in future data analyses to present that essence of the two items *(Stevens 1986)*. In doing so, the two variables have been reduced to one factor, which is a linear combination of the two variables. (Details about computational aspects of PCA can be found elsewhere *(Johnson 1998; Stevens 1986)*.) Basically, the extraction of principal components amounts to a variance maximization rotation of the original variable space. The rotation is to maximize the variance of the new variable (factor) while minimizing the variance around the factor *(Johnson 1998; Stevens 1986)*.

4.2 Reasons for Using Principal Components Analysis

There are several reasons for using the PCA technique *(Johnson 1998)*:

***1. Data Screening*:** Principal components analysis is perhaps most useful for screening multivariate data. For almost all data analysis situations, PCA can be recommended as a first step. It can and should be performed on a set of data prior to performing any other kinds of multivariate analyses. Follow-up analyses on the principal components are useful for checking assumptions that a researcher might make about a set of multivariate data and for identifying and locating possible outliers in the data. If other abnormalities occur in a multivariate data set, PCA can help reveal them.

***2. Clustering*:** Principal components analysis is also helpful whenever a researcher wants to group experimental units into subgroups of similar types. It can be used to help cluster experimental units into subgroups or for verifying the results of clustering programs.

***3. Discriminate Analysis*:** Discriminate analysis programs require that an estimate of the variance-covariance matrix be inverted to develop a discrimination rule. If only a small sample of experimental units from each candidate population is available, less than the number of response variables being measured, the estimated variance-covariance matrix cannot be inverted, and discriminate analysis programs will fail. A PCA revealed that a few principal components contained almost all the information that was available in the original variables. Values for the principal components were obtained for each experimental unit, and these new variables were used as input variables to a discriminate analysis program. The estimated variance-covariance matrix of the new variables could be inverted, and the discriminate analysis program was able to produce a discrimination rule for classifying observations.

*4. **Regression***: It is well known that multiple regression can be misleading when predictor variables are highly correlated in some fashion. This has been referred to as multicollinearity among the predictor variables. Principal component analysis can help determine whether multicollinearity occurs among the predicator variables. PCA in this study was carried out for data screening and regression analysis.

4.3 PCA Analysis Results

In this study, PCA was used to select a group of Superpave mixture constituent parameters that may be used to predict the value of VA, VMA, in-place pavement density, and TSR. PCA was carried out by the Statistical Analysis System (SAS) software *(SAS 1989)*. It should be noted that the PCA results would not be the only basis to select the key factors, because this study of Superpave volumetric properties is not a purely mathematical problem. Engineering judgement should also be used in the process.

In the first step, the bivariate correlation coefficients were computed for each pair of variables. The studied variables were separated into subgroups so that variables within a subgroup are highly correlated with each other.

The correlation coefficient between two variables is a measure of the degree of linear association between the two variables. If the observations of two random variables are fitted with the least squares method, the ratio of explained variance to the total variance is called the coefficient of determination *(R^2)*. This represents the fraction of the total variation that is explained by the estimated linear relationship. The correlation coefficient *(r)* is the square root of the coefficient of determination. R^2 values always lie between 0 and 1. The higher the R^2 value is, the stronger the statistical relationship. An R^2 of 1 indicates a perfect correlation between a pair of variables.

Figure 4.1 shows the correlation matrix based on all observations of the independent variables from all projects. Table 4.1 tabulates the variable symbols and names. In total, 207 data sets out of 709 were included in this study due to the missing data mentioned earlier. All correlation coefficients that were 0.5 or greater in magnitude have been underlined. In this way, it is easier to form the first subgroup by finding two variables that are most highly correlated with each other. The correlation coefficient between percent retained on the 2.36 mm (#8) sieve and percent retained on the 1.18 mm (#16) sieve was 0.98. Again, the correlation coefficient between percent retained on the 1.18 mm (#16) sieve and percent retained on the 0.6 mm (#30) sieve was 0.97. Also, the correlation coefficient between percent retained on the 2.36 mm (#8) sieve and percent retained on the 0.6 mm (#30) sieve was 0.93. These three variables should definitely be in the same group because all three are

	PB	NMAX	NMIN	R34	R12	R38
PB	1.0000	0.4466	0.0572	-.6005	-.4652	-.5397
NMAX	0.4466	1.0000	0.2814	-.2665	-.0984	-.1882
MMIN	0.0572	0.2814	1.0000	-.0386	-.3012	-.4113
R34	-.6005	-.2665	-.0386	1.0000	0.5394	0.6048
R12	-.4652	-.0984	-.3012	0.5394	1.0000	0.9396
R38	-.5397	-.1882	-.4113	0.6048	0.9396	1.0000
R8	-.4372	-.3133	-.7888	0.4438	0.5125	0.6932
R16	-.4155	-.2946	-.7640	0.4665	0.5792	0.7469
R30	-.4512	-.2730	-.6663	0.5353	0.6995	0.8409
R50	-.4583	-.2406	-.5722	0.5598	0.7605	0.8778
R200	-.6723	-.2838	0.1159	0.6525	0.4196	0.5252
SE	-.4530	-.1745	-.2541	0.5501	0.7586	0.8029
FAA	0.5302	0.1546	-.4970	-.5692	-.3070	-.3462
CAA	0.4733	0.3046	0.0068	-.3762	0.2134	0.0173
DP	0.5090	0.1743	-.2159	-.5521	-.2938	-.3964

	R8	R16	R30	R50	R200	TSR
PB	-.4372	-.4155	-.4512	-.4583	-.6723	-.3774
NMAX	-.3133	-.2946	-.2730	-.2406	-.2838	-.1387
MMIN	-.7888	-.7640	-.6663	-.5722	0.1159	-.1294
R34	0.4438	0.4665	0.5353	0.5598	0.6525	0.2116
R12	0.5125	0.5792	0.6995	0.7605	0.4196	0.2945
R38	0.6932	0.7469	0.8409	0.8778	0.5252	0.3035
R8	1.0000	0.9841	0.9254	0.8490	0.3900	0.2630
R16	0.9841	1.0000	0.9710	0.9127	0.4138	0.2472
R30	0.9254	0.9710	1.0000	0.9761	0.4946	0.2420
R50	0.8490	0.9127	0.9761	1.0000	0.5384	0.2328
R200	0.3900	0.4138	0.4946	0.5384	1.0000	0.2641
SE	0.5655	0.6530	0.7805	0.8212	0.5454	0.2150
FAA	-.0009	-.0581	-.2005	-.2777	-.7576	-.1146
CAA	-.4005	-.3277	-.2218	-.1387	-.5007	-.1536
DP	-.2757	-.2995	-.3778	-.4224	-.9410	-.2170

	SE	FAA	CAA	DP
PB	-.4530	0.5302	0.4733	0.5090
NMAX	-.1745	0.1546	0.3046	0.1743
MMIN	-.2541	-.4970	0.0068	-.2159
R34	0.5501	-.5692	-.3762	-.5521
R12	0.7586	-.3070	0.2134	-.2938
R38	0.8029	-.3462	0.0173	-.3964
R8	0.5655	-.0009	-.4005	-.2757
R16	0.6530	-.0581	-.3277	-.2995
R30	0.7805	-.2005	-.2218	-.3778
R50	0.8212	-.2777	-.1387	-.4224
R200	0.5454	-.7576	-.5007	-.9410
SE	1.0000	-.4922	0.0027	-.4725
FAA	-.4922	1.0000	0.3182	0.7265
CAA	0.0027	0.3182	1.0000	0.4541
DP	-.4725	0.7265	0.4541	1.0000

Figure 4.1 Correlation Matrix from SAS

Table 4.1 Variable Symbols and Names

Variable Symbol	Name
PB	Asphalt Binder Content (%)
NMAX	%G_{mm} @ N_{max}
NMIN	%G_{mm} @ N_{ini}
R34	% Retained on 19 mm sieve
R12	% Retained on 12.5 mm sieve
R38	% Retained on 9.5 mm sieve
R8	% Retained on 2.36 mm sieve
R167	% Retained on 1.18 mm sieve
R30	% Retained on 0.6 m sieve
R50	% Retained on 0.3 m sieve
R200	% Retained on 0.075 m sieve
SE	Sand Equivalent (%)
FAA	Fine Aggregate Angularity (%)
CAA	Coarse Aggregate Angularity (%)
DP	Dust Proportion

highly correlated with one another. It is to be noted that the percent retained on the 0.3 mm (#50) sieve should also be included in this subgroup since it had correlation coefficients of 0.85, 0.91, 0.97 with percent retained on the 2.36 mm (#8) sieve, percent retained on the 1.18 mm (#16) sieve and percent retained on the 0.6 mm (#30) sieve, respectively. Further examination of the correlation matrix revealed that none of the other variables appeared to belong to this first group of variables.

A second group of variables was formed with the variables percent retained on the

0.075 mm (#200) sieve, fine aggregate angularity, and dust proportion. The correlation coefficients between successive pairs of these variables were 0.76, 0.94, and 0.73, respectively. No other variable appeared to belong to this subgroup.

A third group of variables was formed by including percent retained on the 19 mm (3/4") sieve, percent retained on the 12.5 mm (1/2") sieve, and percent retained on the 9.5 mm (3/8") sieve. The correlation coefficients between successive pairs of these variables were 0.54, 0.60, and 0.94, respectively. Another important reason that these three variables should be included in a subgroup was that these three sieve sizes are normally used to define the maximum and the nominal maximum sieve sizes for the Superpave mixtures included in this study.

Sand equivalent value was somewhat correlated with many of the variables in Groups 1 and 3. It could not be assigned to Group 1 since the correlation coefficients with many of the variables in Group 1 were much lower than the correlation coefficients among the other variables that had previously been assigned to Group 1. Also, it does not have any physical relationship to the variables in Group 3. Thus, it was decided keep the sand equivalent value independent of the two groups, and it was placed in a group by itself.

Asphalt binder content also had some correlation with two of the variables in Group 3: correlation coefficients of 0.60 and 0.54 with percent retained on the 19 mm (3/4") sieve and percent retained on the 9.5 mm (3/8") sieve, respectively, but only 0.47 with percent retained on the 12.5 mm (1/2") sieve. Thus, it was not included in Group 2 and was used to form a group by itself.

Out of the variables studied for the Superpave mixtures, every variable had been assigned to a subgroup except for $\%G_{mm}$ @ N_{max} (NMAX), $\%G_{mm}$ @ N_{ini} (NMIN), and coarse aggregate angularity (CAA). None of these variables were highly correlated with any other variable, and hence, each was placed into a group by itself.

To summarize, the final grouping of the variables were:

Group 1: % retained on the 2.36 mm (#8) sieve, % retained on the 1.18 mm (#16) sieve, % retained on the 0.6 mm (#30) sieve, and % retained on the 0.3 mm (#50) sieve

Group 2: % retained on the 0.075 mm (#200) sieve, fine aggregate angularity, and dust proportion

Group 3: % retained on the 19 mm (3/4") sieve, % retained on the 12.5 mm (1/2") sieve, and % retained on the 9.5 mm (3/8") sieve

Group 4: Sand equivalent

Group 5: Asphalt binder content

Group 6: $\%G_{mm}$ @ N_{max}

Group 7: $\%G_{mm}$ @ N_{ini}

Group 8: Coarse aggregate angularity

Table 4.2 shows the eigenvalues from the PCA results. The eigenvalues of a $p*p$ matrix $\mathbf{A}$ are the solutions to the following determinant equation: $|\mathbf{A} - \lambda\mathbf{I}| = 0$, in which, $\mathbf{I}$ is the identity matrix of order p. The table consists of four columns. The first column gives the eigenvalues. The second column lists the difference between successive eigenvalues. This difference has limited use. The third and fourth columns give the proportion of the total variation, which is accounted for by successive principal components, and the cumulative proportion of the total variation, which is accounted for by that principal component, and all of the previous ones, respectively. As mentioned earlier, a principal component/factor in

Table 4.2 **Significant Eigenvalues of the Correlation Matrix (Extraction: Principal Component Analysis)**

Factor	Eigenvalue	Difference Eigenvalue	% Total Variance	% Cumulative Variance
1	7.90366	4.87644	0.493979	0.49398
2	3.02722	1.33949	0.189201	0.68318
3	1.68773	0.70587	0.105483	0.78866
4	0.98186	0.15878	0.061366	0.85003

PCA is a linear combination of all variables.

According to Kaiser's rule of thumb, factors with eigenvalues greater than or close to 1 are significant. Results in Table 4.2 indicate that four principle components (or factors) are significant. A plot of these eigenvalues is shown in Figure 4.2. From the plot, it is noted when the plot tends to level off, those eigenvalues are usually close enough to zero that they can be ignored. At the very least, the smaller ones are probably measuring nothing but the random noise which is very difficult to interpret. The plot also shows that the first four factors have eigenvalues greater than or close to 1.0. The first factor explained 49 percent of the variation on the system. The second, third, and fourth factors accounted for 18.9 percent, 10.5 percent, and 6.1 percent of the variation, respectively. The four factors together accounted for 85 percent of the total variance, so it appears that the observation data tend to fall within a 4-dimensional subspace of the 15-dimensional space. After consultation with statisticians and KDOT engineers, it was decided that an 8-dimensional subspace obtained from the correlation matrix analysis would be used for future study instead of the 4-dimensional subspace based on the analysis of eigenvalues. This was felt necessary to keep

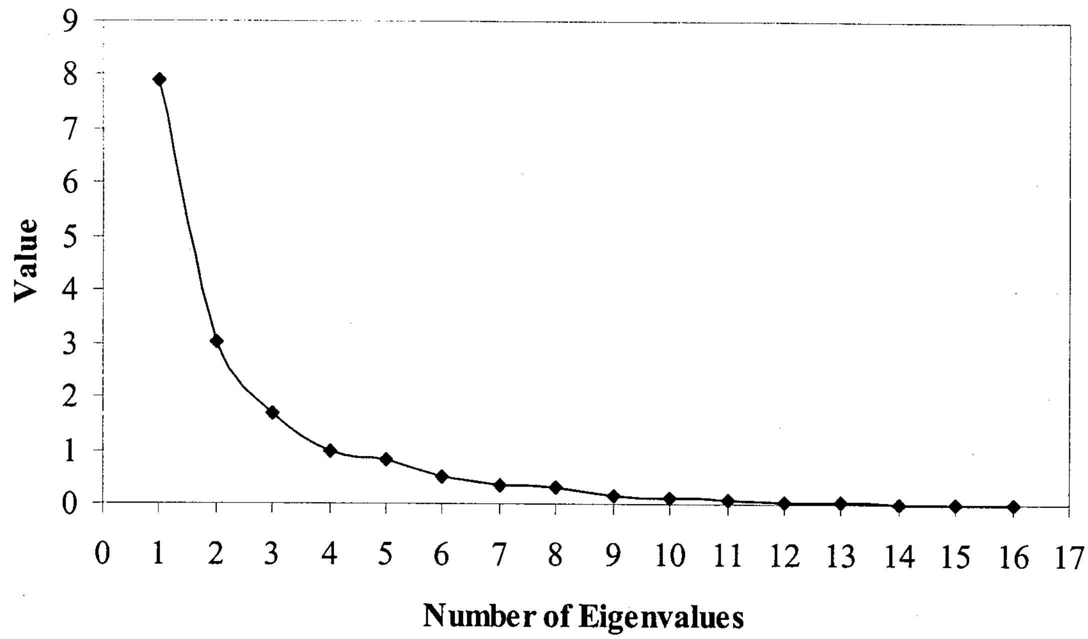

Figure 4.2 Plot of Eigenvalues

the independent variables selected for the study in the multiple correlation analysis (MCA), and also because MCA can also be used to eliminate the less important variables based on the significance analysis.

There is no obvious interpretation for the first four factors in the PCA. Any such interpretation must come from an examination of the factor loadings in Table 4.3. The factor loadings are normalized to have length 1, which indicates that the sum of the squares of each factor must be equal to 1. The variables with the larger factor loadings (absolute value) have stronger relationships. The variables in this study, which tend to have strong relationships with the first factor, are percent retained on the 2.36 mm (#8) sieve, percent retained on the 1.18 mm (#16) sieve, percent retained on the 0.6 mm (#30) sieve, and percent retained on

Table 4.3 Factor Loadings from Principal Components

Variable Symbol	Factor			
	1	2	3	4
PB	-.244312	0.214634	0.151666	-.308586
NMAX	-.130860	0.030720	0.386782	-.273532
NMIN	-.156954	-.469696	0.222184	-.003674
R34	0.257537	-.193965	0.020310	-.026896
R12	0.272223	0.084491	0.405708	0.185222
R38	0.316614	0.088311	0.263040	0.084084
R8	0.295760	0.239707	-.235536	-.110637
R16	0.308572	0.237048	-.152445	-.140462
R30	0.328847	0.187410	-.010814	-.139291
R50	0.330276	0.147324	0.087908	-.131070
R200	0.260201	-.343347	-.046778	-.098387
SE	0.293224	0.005918	0.287427	-.070860
FAA	-.119862	0.223545	0.585895	0.166266
CAA	-.119862	0.223545	0.585895	0.166266
DP	-.214975	0.369949	0.020750	0.178497

the 0.3 mm (#50) sieve. The variables that have strong relationships with the second factor are percent retained on the 0.075 mm (#200) sieve, fine aggregate angularity, and dust proportion. The variable with relationship with the third factor is the coarse aggregate angularity. The fourth factor is strongly related to the asphalt binder content. It is interesting to note that these four groups of variables are similar to the groups of variables obtained from the correlation analysis.

4.4 Re-analysis (without SM-2A)

A new PCA was carried out because two projects, Projects 3 and 9, in the Table 3.1 containing SM-2A, did not have good quality data. When the data from these two projects was excluded, only 136 data sets were used, compared to 207 with SM-2A. The correlation matrix of PCA is shown in Figure 4.3. The variable groups using the same method as earlier are:

Group 1: percent retained on the 0.6 mm (#30) sieve, and percent retained on the 0.3 mm (#50) sieve, percent retained on the 0.075 mm (#200) sieve, dust proportion, sand equivalent, fine aggregate angularity, and coarse aggregate angularity

Group 2: Asphalt binder content, percent retained on the 19 mm (3/4") sieve, and percent retained on the 12.5 mm (1/2") sieve

Group 3: percent retained on the 2.36 mm (#8) sieve, and percent retained on the 1.18 mm (#16) sieve

Group 4: percent retained on the 9.5 mm (3/8") sieve

Group 5: $\%G_{mm}$ @ N_{max}

Group 6: $\%G_{mm}$ @ N_{ini}

	PB	NMAX	NMIN	R34	R12	R38
PB	1.0000	0.5347	-.4806	-.5750	-.7269	-.0967
NMAX	0.5347	1.0000	0.0271	-.2251	-.2580	-.0084
NMIN	-.4806	0.0271	1.0000	0.5972	0.4945	0.1365
R34	-.5750	-.2251	0.5972	1.0000	0.6573	0.1811
R12	-.7269	-.2580	0.4945	0.6573	1.0000	0.2123
R38	-.0967	-.0084	0.1365	0.1811	0.2123	1.0000
R8	-.4679	-.2909	-.1257	0.2907	0.5721	0.1598
R16	-.6433	-.4576	0.2616	0.5294	0.7194	0.2057
R30	-.7291	-.4701	0.6315	0.6860	0.7496	0.2211
R50	-.7261	-.4541	0.6869	0.7050	0.7354	0.2224
R200	-.7195	-.4246	0.6415	0.6681	0.7239	0.1906
SE	-.7337	-.3761	0.7542	0.6807	0.6618	0.1573
FAA	0.6914	0.3536	-.8103	-.7233	-.6772	-.2213
CAA	0.7383	0.3577	-.8482	-.7159	-.6695	-.1988
DP	0.6205	0.3460	-.6123	-.6258	-.6537	-.1936

	R8	R16	R30	R50	R200	TSR
PB	-.4679	-.6433	-.7291	-.7261	-.7195	-.3674
NMAX	-.2909	-.4576	-.4701	-.4541	-.4246	-.1285
NMIN	-.1257	0.2616	0.6315	0.6869	0.6415	0.0720
R34	0.2907	0.5294	0.6860	0.7050	0.6681	0.1588
R12	0.5721	0.7194	0.7496	0.7354	0.7239	0.3540
R38	0.1598	0.2057	0.2211	0.2224	0.1906	-.0058
R8	1.0000	0.8684	0.5704	0.4888	0.5167	0.2835
R16	0.8684	1.0000	0.8880	0.8338	0.8344	0.2676
R30	0.5704	0.8880	1.0000	0.9906	0.9651	0.2203
R50	0.4888	0.8338	0.9906	1.0000	0.9779	0.2053
R200	0.5167	0.8344	0.9651	0.9779	1.0000	0.2432
TSR	0.2835	0.2676	0.2203	0.2053	0.2432	1.0000
FAA	-.3204	-.6877	-.9181	-.9323	-.8898	-.0933
CAA	-.2254	-.6043	-.8778	-.9094	-.8693	-.1299
DP	-.5276	-.8322	-.9425	-.9520	-.9755	-.2353

	SE	FAA	CAA	DP
PB	-.7337	0.6914	0.7383	0.6205
NMAX	-.3761	0.3536	0.3577	0.3460
NMIN	0.7542	-.8103	-.8482	-.6123
R34	0.6807	-.7233	-.7159	-.6258
R12	0.6618	-.6772	-.6695	-.6537
R38	0.1573	-.2213	-.1988	-.1936
R8	0.3197	-.3204	-.2254	-.5276
R16	0.6501	-.6877	-.6043	-.8322
R30	0.8663	-.9181	-.8778	-.9425
R50	0.8790	-.9323	-.9094	-.9520
R200	0.8408	-.8898	-.8693	-.9755
SE	1.0000	-.8964	-.9504	-.8139
FAA	-.8964	1.0000	0.9548	0.8468
CAA	-.9504	0.9548	1.0000	0.8208
DP	-.8139	0.8468	0.8208	1.0000

Figure 4.3 Correlation Matrix from SAS without SM-2A

Using engineering judgement, it is not an improvement to subdivide the independent variables as above because variables with no physical connection were categorized in the same subgroup. Additional data would improve the results from the PCA analysis as long as the data was from the field tests, even though the quality of the mixture was poor. The more data that is used, the more results would be reasonably obtained both from statistical and an engineering standpoint.

5.0 MULTIPLE CORRELATION ANALYSIS

5.1 Background

Multiple correlation analysis (MCA) provides a great deal of important information. It isolates the key variables which have the most significant effect on the system. It also reports the statistical certainty and relative weight of each of these variables. The major advantage of MCA, however, is the ability to deal with a large amount of data containing a large set of variables.

The basic premise of MCA is finding a correlation between a dependent variable and one or more independent variables. In its simplest form, a positive correlation between two variables means that as one variable is increased, the other tends to increase. If the data is affected by more than one independent variable, multiple correlation (also known as multiple regression) analysis determines the effects of these independent variables, and also the effects of any interactions among them. The result is an equation, which can be called a model, and describes the effects of the independent variables on the dependent variable.

In order to quantify the effect of the key predictor variables obtained from PCA on each of the four responses variables: i.e. Va, VMA, in-place pavement density, and TSR; the assumption was made that each response variable, or "Y" satisfied the following functional relationship:

$$Y = \boldsymbol{F}\,\{\text{Binder Content, Aggregate gradation, Sand Equivalent, ...}\} \qquad \text{... (5.1)}$$

although the explicit form of this function was unknown. Using Taylor's theorem from

Calculus, the function F has partial derivatives with respect to the variables in the argument. This function is estimated using an expression which is linear in the coefficients. The model then takes the following form: *(Schwenke 1998)*

$$Y = aX_1 + bX_2 + cX_3 + \ldots \qquad (5.2)$$

where Y is the dependent variable, X_1, X_2 and X_3 are the independent variables, and a, b, and c are the correlation coefficients.

In some cases, two or more independent variables will have some sort of interaction in the system being studied. An interaction is said to exist between two independent variables if the effect of one depends on the effect of the other. For example, X_2 may have a more significant effect at a high level of X_1, than at a low level of X_1. In order to account for this effect, it is possible to create new variables that are combinations of the original set of independent variables. Interaction between two variables is often crucial in multiple correlation analysis. The most common form of an interaction is the product of two variables. These can then be added to the model, when appropriate, creating an equation of the following form *(Schwenke 1998)*:

$$Y = aX_1 + bX_2 + I_{12}X_1 * X_2 + cX_3 \qquad (5.3)$$

where I_{12} represents the correlation coefficient of the interaction between the variables X_1 and X_2. Since there is virtually a large number of possible interactions, the present analysis includes the interactions between two variables only.

5.2 MC Software Program

Multiple Correlation (MC) is a powerful commercial software *(MC 1991)*. MC can be used to determine the relationship between a dependent variable (Y) and one or more independent variables (X's) and their interactions so that Y can be predicted from the X's *(MC 1991)*. MC is intended to extract the maximum information from a set of data and can:

- distinguish independent variables which significantly affect the dependent variable from those that do not (superfluous variables)
- establish a functional relationship which quantifies how the significant independent variables affect the dependent variable
- permit predictions of the dependent variable from a functional relationship instead of guessing and/or continually running experiments with different variables
- indicate prediction accuracy
- ascertain if all the variability in the dependent variable has been explained, and if it has not been, determine what to do next
- reveal optimum operating conditions
- reduce testing.

5.3 Criteria to Build A Model

Every model is built on the framework of statistical information. Using multiple correlation analysis (MCA), the arguments were determined via least squares theory that were statistically significantly based on the following four statistics *(MC 1991)*:

1. Correlation Coefficient **:** The correlation coefficient reflects the magnitude and sign of the effect of a variable. A positive sign of a correlation coefficient predicts an increase in the dependent variable as the independent variable is increased.

***2. t-Value*:** The t-value represents the relative certainty that a given independent variable has an effect on the dependent variable. Specifically, it is the magnitude of the correlation coefficient divided by the standard deviation of the variable to which it pertains. The t-value for the ith variable is given by:

$$t = \frac{b_i}{S(b_i)} \qquad (5.4)$$

where t = indicator of the significance of the ith independent variable,

b_i = coefficient for the ith independent variable, and

$S(b_i)$= standard deviation of the ith independent variable.

In general, a t-value with an absolute value greater than or equal to two (2), corresponding to a 90% certainty, is considered to be statistically significant. It is important to note that the sign of the t-value relates only to the sign of the effect, not the certainty involved with a given variable. Also, a variable with a t-value of less than 2 is not considered to be significant. The goal of MCA was to have a correlation model with all variables in the model having absolute t-values greater than or equal to 2.

***3. R^2 Value*:** There are two types of R^2 calculations. Both range from zero (0) to one (1). The first is the R^2 for the model. This is also known as the coefficient of multiple determination. This R^2 value reflects the amount of the total variation of the data which is described by the model. A value of one would occur if all of the variation is explained by a given model, while a value of zero indicates none of the variation is explained. Any variation that is not explained could be the result of the effects of variables not included in the model, errors in the data, or any number of uncontrolled and uncontrollable effects (sometimes referred to as noise in the data). It is calculated by:

$$R^2 = 1 - \frac{(n-p-1)(S_{y,x})^2}{(n-1)(S_{total})^2} \qquad \text{.. (5.5)}$$

where: n = number of rows in the data set,

p = number of terms in the model,

$S_{y,x}$ = standard deviation of the dependent variable, and

S_{total} = total variation of the model.

R^2 is the only criteria in determining how good a model is. The model selected is usually the one with the largest R^2. However, R^2 is also a random variable based on sampled information, and the model associated with the absolute maximum R^2 may not always be the most relevant model *(Wesolowsky 1976)*. Besides, R^2 is always increased by including additional variables even when the new variable has very little predictive power. Therefore, it is also necessary to look at the Mean Square Error (MSE) when determining the quality of a model.

The second type of R^2 is calculated for each independent variable. As a model is built, the analysis software (MC) also provides an R^2 value for each independent variable in the model. This value is a measure of how well a particular variable correlates with other variables currently in the model. It is used to help decide which of two variables with the same t-value should be included in the model.

4. Mean Square Error (MSE): Every linear model has an associated MSE estimating variance (σ^2). MSE is used to construct all confidence intervals and test statistics. The smallest MSE will result in the narrowest confidence intervals and largest test statistics. The model with the smallest MSE involving the least number of independent variables can be considered as the best model. However, the model with the absolute smallest MSE may not provide the best intuitive or explainable model. A model providing a slightly larger MSE, but with terms included in the model that are more relevant to the problem, may be more desirable *(Ott 1993)*.

5.4 Building the Model

There are several possible strategies for building the model. A forward selection procedure, available in MC, was used to determine which independent variables are closely related to the air voids, voids in mineral aggregate, in-place pavement density, and moisture sensitivity (TSR).

The strategy selected in this study was to start with no variables in the regression equation or model. The first independent variable considered for the model was the most significant one with the highest absolute t-value, provided its presence in the model would be physically meaningful. At this point, the remaining variables were individually reevaluated to determine what their t-values would be if they were included in the model. The variable with the highest t-value was then added to the model, if it was physically plausible, and this process was repeated until all variables not in the model had t-values lower than 2. This approach made it possible to evaluate the effects of a very large number of possible significant variables individually, and to find the ones that were the most significant.

After statistically significant variables were determined, first-order interactions were included in the model as additional independent variables. Then MC was to used to evaluate each member of this extended set of variables to determine what interaction term should be included in the models based on the t-value, while keeping all the selected independent variables. However, some of the independent variables then had t-values of lower than two because of added interaction terms. There were exceptions to this process under the following circumstances:

(i) Variables with high t-values might have little physical relevance or the sign of their correlation was opposite to the accepted understanding of the engineering concept, and

(ii) Too many variables were included in the model to preserve a reasonable degree of freedom. In other words, it was important not to overspecify the model variables.

5.5 MCA Results

Based on the PCA results and by consultation with KDOT engineers, eight parameters were selected from the subgroups as independent variables: percent retained on the 0.6 mm (#30) sieve, dust proportion, one sieve size smaller than nominal maximum size of the analyzed mixture, sand equivalent, asphalt binder content, $\%G_{mm}$ @ N_{max}, $\%G_{mm}$ @ N_{min}, and coarse aggregate angularity. The final regression equations with the statistical information (for air void, void in mineral aggregate, in-place pavement density, and moisture sensitivity) are as below:

Change Order Projects:

- Tables 5.1 to 5.4: 9.5 mm nominal maximum size mixture (SM-1T)

• Tables 5.5 to 5.8: 12.5 mm nominal maximum size mixture (SM-2A)

• Tables 5.9 to 5.12: 19 mm nominal maximum size mixture without Reclaimed Asphaltic Pavement (RAP) (SM-2C)

• Tables 5.13 to 5.16: 19 mm nominal maximum size mixture with RAP (SR-2C)

Let Projects:

• Tables 5.17 to 5.19: 19 mm nominal maximum size mixture without RAP (SM-2C)

• Tables 5.20 to 5.22: 19 mm nominal maximum size mixture with RAP (SR-2C)

The symbols in parenthesis are the mixture symbols used by KDOT.

Table 5.23 summarizes R^2 values from all regression equations. It indicates that very good predictive equations can be found using the predictors isolated in this study for the air voids at N_{design} and VMA, but not for the in-place pavement density and TSR. R^2 values for air void in all cases are greater than 0.70 and R^2 values for VMA vary from 0.67 to 0.90. No statistically significant equations were obtained for the in-place pavement density with R^2 values ranging from 0.43 to 0.44 for the smaller-size mixtures (9.5 mm and 12.5 mm) and 0.05 to 0.36 for the large-size (19 mm) mixtures. This is somewhat expected since the in-place pavement density also depends upon the mixture temperature, compactive effort, etc., in addition to the mixture constituents. The difference in R^2 values between smaller-size and large-size mixtures also indicates that the compaction of large-size mixtures is different from the compaction of smaller-size mixtures. This is obvious in the field when the large-size Superpave mixtures tend to cool off fast due to lack of sandy materials. The regression equations for TSR have R^2 values of 0.52 for the smaller-size mixtures and 0.76 to 0.80 for the larger-size mixtures. The difference of R^2 values between these mixtures implies that

Table 5.1 **Multiple Regression Equation Information for Va of SM-1T (Change Order)**

Variable	Coeff.	t	p	R^2
Intercept	1767.57	3.62	0.001	
Pb	-0.804	-2.76	0.009	0.42
$\%G_{mm}@N_{max}$	-1.137	-5.25	0.0001	0.39
%Retained on 0.6 mm	-18.445	-3.34	0.002	1.00
Sand Equivalent	20.409	-3.50	0.001	1.00
Dust Proportion	2.024	1.54	0.13	0.90
Sand Equivalent*%Retained on 0.6 mm	0.229	3.40	0.002	1.00
Model Statistics: $R^2 = 0.74$ MSE = 0.21 F= 16.04 p=0.0001 N = 39				

Table 5.2 **Multiple Regression Equation Information for VMA of SM-1T (Change Order)**

Variable	Coeff.	t	p	R^2
Intercept	2251.48	2.84	0.008	
Pb	0.968	4.37	0.0001	0.44
$\%G_{mm}@N_{max}$	-15.959	-2.01	0.053	1.00
%Retained on 0.6 mm	-25.000	-2.67	0.012	1.00
Sand Equivalent	-8.578	-2.04	0.005	1.00
Dust Proportion	-0.523	-0.55	0.587	0.91
$\%G_{mm}@N_{max}$*%Retained on 0.6 mm	0.180	1.90	0.066	1.00
Sand Equivalent*%Retained on 0.6 mm	0.094	1.92	0.063	1.00
Model Statistics: $R^2 = 0.90$ MSE = 0.11 F=39.18 p=0.0001 N= 39				

Table 5.3 **Multiple Regression Equation Information for In-place Pavement Density of SM-1T (Change Order)**

Variable	Coeff.	t	p	R^2
Intercept	134.03	16.77	0.0001	
Sand Equivalent	-0.535	-5.54	0.0001	0.0
Model Statistics: $R^2 = 0.44$ MSE = 0.81 F=30.64 p=0.0001 N=39				

Table 5.4 **Multiple Regression Equation Information for TSR of SM-1T (Change Order)**

Variable	Coeff.	t	p	R^2
Intercept	-60.53	-2.25	0.031	
$\%G_{mm}@N_{min}$	0.351	1.93	0.061	0.06
%Retained on 0.6 mm	-0.715	-3.30	0.002	0.73
Sand Equivalent	2.145	5.60	0.0001	0.73
Model Statistics: $R^2 = 0.52$ MSE = 3.45 F=13.04 p=0.0001 N=39				

Table 5.5 Multiple Regression Equation Information for Va of SM-2A (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	100.42	30.306	0.0001	
Pb	-0.569	-4.28	0.0004	0.43
$\%G_{mm}@N_{max}$	-0.387	-4.53	0.0002	0.88
$\%G_{mm}@N_{min}$	-0.580	-6.13	0.0001	0.87
%Retained on 0.6 mm	-0.055	-2.88	0.0093	0.40
Model Statistics: $R^2 = 0.98$ MSE = 0.01 F=286.99 p=0.0001 N=24				

Table 5.6 Multiple Regression Equation Information for VMA of SM-2A (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	56.41	7.95	0.0001	
Pb	1.051	3.61	0.0016	0.47
$\%G_{mm}@N_{min}$	-0.530	-6.04	0.0001	0.35
%Retained on 9.5 mm	-0.038	-1.85	0.0079	0.25
Model Statistics: $R^2 = 0.72$ MSE = 0.11 F=17.72 p=0.0001 N=24				

Table 5.7 Multiple Regression Equation Information for In-place Pavement Density of SM-2A (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	115.01	19.44	0.0001	
Sand Equivalent	-0.292	-4.02	0.0006	0.16
Dust Proportion	3.191	-2.30	0.032	0.16
Model Statistics: $R^2 = 0.43$ MSE = 0.34 F=8.34 p=0.002 N=24				

Table 5.8 Multiple Regression Equation Information for TSR of SM-2A (Change Order)

Variable	Coeff.	t	p	R^2
$\%G_{mm}@N_{max}$	-7.420	-3.73	0.0012	0.84
$\%G_{mm}@N_{min}$	4.408	1.94	0.066	0.84
Sand Equivalent	-3.812	-15.72	0.0001	0.03
Model Statistics: $R^2 = 0.52$ MSE = 4.38 F=92.88 p=0.0001 N=24				

Table 5.9 Multiple Regression Equation Information for Va of SM-2C (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	25.99	2.68	0.009	
$\%G_{mm}@N_{max}$	-0.639	-5.49	0.0001	0.66
$\%G_{mm}@N_{min}$	-0.098	-1.00	0.322	0.67
%Retained on 12.5 mm	-0.047	-3.36	0.001	0.09
%Retained on 0.6 mm	0.549	10.34	0.0001	0.12
Model Statistics: $R^2 = 0.75$ MSE = 0.22 F=74.62 p=0.0001 N=106				

Table 5.10 Multiple Regression Equation Information for VMA of SM-2C (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	65.88	10.52	0.0001	
$\%G_{mm}@N_{min}$	-0.555	-7.72	0.0001	0.00
Dust Proportion	-4.547	-12.00	0.0001	0.00
Model Statistics: $R^2 = 0.67$ MSE = 0.35 F=106.61 p=0.0001 N=106				

Table 5.11 Multiple Regression Equation Information for In-place Pavement Density of SM-2C (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	76.35	4.30	0.0001	
$\%G_{mm}@N_{min}$	0.474	3.60	0.0005	0.09
%Retained on 0.6 mm	-0.277	-2.39	0.019	0.09
Model Statistics: $R^2 = 0.20$ MSE = 1.09F=13.25 p=0.0001 N=106				

Table 5.12 Multiple Regression Equation Information for TSR of SM-2C (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	10269	1.78	0.078	
$\%G_{mm}@N_{max}$	286.876	4.71	0.0001	1.00
$\%G_{mm}@N_{min}$	-176.162	-2.66	0.0091	1.00
%Retained on 0.6 mm	-140.983	-5.25	0.0001	1.00
Sand Equivalent	-233.233	-4.23	0.0001	1.00
Dust Proportion	1008.936	-5.82	0.0001	1.00
%Retained on 0.6 mm*Sand Equivalent	1.710	5.29	0.0001	1.00
$\%G_{mm}@N_{max}$*Sand Equivalent	-2.363	-4.19	0.0001	1.00
$\%G_{mm}@N_{max}*\%G_{mm}@N_{min}$	-1.071	-2.38	0.019	1.00
Sand Equivalent*$\%G_{mm}@N_{min}$	3.413	5.20	0.0001	1.00
Sand Equivalent*Dust Proportion	12.216	5.85	0.0001	1.00
Model Statistics: $R^2 = 0.80$ MSE = 8.06 F=37.94 p=0.00021 N=106				

Table 5.13 **Multiple Regression Equation Information for Va of SR-2C (Change Order)**

Variable	Coeff.	t	p	R^2
Intercept	1390.49	1.97	0.056	
$\%G_{mm}@N_{min}$	-16.891	-2.07	0.045	1.00
%Retained on 0.6 mm	-16.050	-2.00	0.052	1.00
Dust Proportion	2.041	5.16	0.0001	0.32
$\%G_{mm}@N_{min}$*%Retained on 0.6 mm	0.195	2.10	0.042	1.00
Model Statistics: $R^2 = 0.82$ MSE = 0.23 F=47.62 p=0.0001 N=45				

Table 5.14 **Multiple Regression Equation Information for VMA of SR-2C (Change Order)**

Variable	Coeff.	t	p	R^2
Intercept	1375.80	2.40	0.021	
Asphalt Binder Content	-0.575	3.08	0.004	0.53
$\%G_{mm}@N_{min}$	-16.266	-2.46	0.018	1.00
%Retained on 0.6 mm	-15.803	-2.43	0.020	1.00
Sand Equivalent	0.011	1.96	0.058	0.41
$\%G_{mm}@N_{min}$ *%Retained on 0.6 mm	0.188	2.50	0.017	1.00
Model Statistics: $R^2 = 0.81$ MSE = 0.13 F=34.88 p=0.0001 N=45				

Table 5.15 Multiple Regression Equation Information for In-place Pavement Density of SR-2C (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	146.13	13.45	0.0001	
%Retained on 0.6 mm	-0.606	-4.96	0.0001	0.00
Model Statistics: $R^2 = 0.36$ MSE = 1.08 F=24.61 p=0.0001 N=45				

Table 5.16 Multiple Regression Equation Information for TSR of SR-2C (Change Order)

Variable	Coeff.	t	p	R^2
Intercept	-3603.93	-2.04	0.048	
Asphalt Binder Content	813.631	2.62	0.012	1.00
$\%G_{mm}@N_{min}$	46.279	2.26	0.029	1.00
%Retained on 0.6 mm	-2.619	-4.13	0.002	0.39
Sand Equivalent	-0.223	-3.26	0.0023	0.42
Asphalt Binder Content*$\%G_{mm}@N_{min}$	-9.546	-2.65	0.011	1.00
Model Statistics: $R^2 = 0.76$ MSE = 17.85 F=25.97 p=0.0001 N=45				

Table 5.17 Multiple Regression Equation Information for Va of SM-2C (Let)

Variable	Coeff.	t	p	R^2
Intercept	-73.47	-0.74	0.46	
Pb	-0.279	-1.93	0.057	0.70
$\%G_{mm}@N_{max}$	8.455	8.60	0.0001	1.00
$\%G_{mm}@N_{min}$	-8.658	-8.13	0.0001	1.00
%Retained on 12.5 mm	-0.002	-0.21	0.837	0.91
%Retained on 0.6 mm	2.558	1.87	0.065	1.00
Sand Equivalent	-0.835	-1.74	0.086	1.00
$\%G_{mm}@N_{min}$*%Retained on 0.6 mm	0.083	5.43	0.0001	1.00
$\%G_{mm}@N_{max}$*%Retained on 0.6 mm	-0.100	-8.68	0.0001	1.00
$\%G_{mm}@N_{min}$*Sand Equivalent	0.010	1.73	0.087	1.00
Model Statistics: R^2 = 0.94 MSE = 0.03 F=169.46 p=0.0001 N=104				

Table 5.18 Multiple Regression Equation Information for VMA of SM-2C (Let)

Variable	Coeff.	t	p	R^2
Intercept	-67.16	-0.48	0.636	
Pb	7.952	0.72	0.476	1.00
$\%G_{mm}@N_{max}$	9.551	5.53	0.0001	1.00
$\%G_{mm}@N_{min}$	-9.887	-7.20	0.0001	1.00
%Retained on 12.5 mm	-0.016	-1.94	0.055	0.90
%Retained on 0.6 mm	1.177	1.00	0.322	1.00
Dust Proportion	-1.295	-4.91	0.0001	0.71
$\%G_{mm}@N_{min}$*%Retained on 0.6 mm	0.084	7.51	0.0001	1.00
$\%G_{mm}@N_{max}$*%Retained on 0.6 mm	-0.086	-6.42	0.0001	1.00
$\%G_{mm}@N_{min}$*Pb	0.424	3.69	0.0004	1.00
$\%G_{mm}@N_{max}$*Pb	-0.447	2.96	0.004	1.00
Model Statistics: $R^2 = 0.90$ MSE = 0.03 F=83.92 p=0.0001 N=104				

Table 5.19 Multiple Regression Equation Information for In-place Pavement Density of SM-2C (Let)

Variable	Coeff.	t	p	R^2
Intercept	85.48	24.12	0.0001	
%Retained on 0.6 mm	0.088	2.20	0.030	0.00
Model Statistics: $R^2 = 0.05$ MSE = 1.06 F=4.835 p=0.03 N=104				

Table 5.20 Multiple Regression Equation Information for Va of SR-2C (Let)

Variable	Coeff.	t	p	R^2
Intercept	86.17	4.68	0.0001	
Pb	1.045	1.96	0.054	0.99
$\%G_{mm}@N_{max}$	-1.920	-10.70	0.0001	0.99
$\%G_{mm}@N_{min}$	1.027	10.45	0.0001	0.99
%Retained on 0.6 mm	-0.017	-0.95	0.346	0.84
Sand Equivalent	0.180	3.78	0.0003	0.99
Dust Proportion	19.183	1.25	0.214	1.00
$\%G_{mm}@N_{min}$*Dust Proportion	-1.307	-14.71	0.0001	1.00
$\%G_{mm}@N_{max}$*Dust Proportion	0.883	6.42	0.0001	1.00
Sand Equivalent*Dust Proportion	-0.154	-3.69	0.0004	1.00
Pb*Dust Proportion	-0.974	-2.00	0.049	1.00
Model Statistics: $R^2 = 0.99$ MSE = 0.01 F=552.15 p=0.0001 N=88				

Table 5.21 Multiple Regression Equation Information for VMA of SR-2C (Let)

Variable	Coeff.	t	p	R^2
Intercept	-821.55	-2.67	0.009	
Pb	0.762	5.51	0.0001	0.32
$\%G_{mm}@N_{max}$	-0.395	-5.78	0.0001	0.57
$\%G_{mm}@N_{min}$	6.780	2.81	0.006	1.00
%Retained on 0.6 mm	3.368	2.18	0.032	1.00
Sand Equivalent	11.692	3.01	0.004	1.00
Dust Proportion	-2.147	-6.45	0.0001	0.78
$\%G_{mm}@N_{min}$*Sand Equivalent	-0.092	-3.02	0.003	1.00
%Retained on 0.6 mm*Sand Equivalent	-0.044	-2.29	0.025	1.00
Model Statistics: $R^2 = 0.89$ MSE = 0.04 F=78.48 p=0.0001 N=88				

Table 5.22 Multiple Regression Equation Information for In-place Pavement Density of SR-2C (Let)

Variable	Coeff.	t	p	R^2
Intercept	80.50	2.24	0.028	
$\%G_{mm}@N_{max}$	0.519	2.16	0.033	0.17
%Retained on 0.6 mm	-0.384	-1.83	0.070	0.76
Dust Proportion	-5.212	-3.52	0.001	0.74
Model Statistics: $R^2 = 0.22$ MSE = 1.01 F=8.08 p=0.0001 N=88				

Table 5.23 **Summary of R^2 Values for All Regression Equations**

	9.5 and 12.5 mm mixtures	19 mm mixtures
Va	0.74 to 0.98	0.75 to 0.99
VMA	0.72 to 0.90	0.67 to 0.90
Density (in-place)	0.43 to 0.44	0.05 to 0.36
TSR	0.52 to 0.52	0.76 to 0.80

volumetric properties monitored by KDOT have only casual, not decisive effect on TSR. This conclusion can be supported by practical experience: some mixtures had a perfect volumetric design (which means that the volumetric parameters satisfied all requirements set by KDOT and other agencies), but failed the TSR test. The moisture sensitivity of the Superpave mixtures may be more related to the properties of the asphalt binder than to the asphalt binder content and other factors. It is also important to note that the coarse aggregate angularity does not appear in any of predictive equations presumably due to the fact that all coarse aggregates used on the Superpave projects in Kansas were entirely crushed materials.

5.6 Sensitivity Analysis

Based on the R^2 value analysis in the previous section, only correlation equations for Va and VMA were selected in the sensitivity analysis. In this analysis, the predicted values (air voids at N_{design} and VMA) were plotted against different values of the independent variables obtained from the corresponding equations. The predicted value changes with the levels of a certain independent variable. Three levels of each independent variable, minimum, median, and maximum, from the data set used to formulate these equations were used. All other independent variables were kept fixed.

5.6.1 SM-1T: 9.5 mm Nominal Maximum-Size Mixture (Change Order)

Tables 5.1 and 5.2 indicate that the binder content, percent G_{mm} at N_{max}, percent material retained on the 0.6 mm (#30) sieve, sand equivalent value, dust proportion and the interaction between the sand equivalent and percent material retained on the 0.6 mm (#30) sieve significantly affect the air voids obtained at N_{design} and VMA. For VMA, the interaction between percent G_{mm} at N_{max} and percent material retained on the 0.6 mm (#30) sieve is also significant. These variables should be controlled very precisely in plant production to produce a 9.5 mm (3/8") Superpave mixture with consistent air void and VMA.

Figures 5.1 and 5.2 are the plots showing the predicted values (air voids at N_{design} and VMA) against different values of the independent variables shown in Tables 5.1 and 5.2. Figure 5.1 indicates that with all other factors fixed, the air voids at N_{design} is most sensitive to the changes in percent G_{mm} at N_{max}, percent material retained on the 0.6 mm (#30) sieve and sand equivalent value. A five percent change in the percent material retained on the 0.6 mm (#30) sieve increases the air voids by almost 3%. Very high $\%G_{mm}$ at N_{max} values are also detrimental for the air voids. The air void is not as sensitive to the changes in the binder content as conventional thinking would indicate. This might be because of higher binder contents (6.1 to 7.1%) used on these projects.

The figure also indicates that the increase in dust proportion will increase the air voids. This is also contrary to common beliefs. However, it should be noted that the data used in this analysis was "skewed;" i.e., all air void values were below the 4% target value required in all projects. This probably indicates the benefit of having more dust when the air void is below 4%; some bag house fines could be introduced into the mixture when the binder content is kept unchanged.

Figure 5.2 illustrates that when all other factors are kept constant, VMA is most sensitive to changes in percent material retained on the 0.6 mm (#30) sieve and sand equivalent value. A 5% change in the percent of material retained on the 0.6 mm (#30) sieve

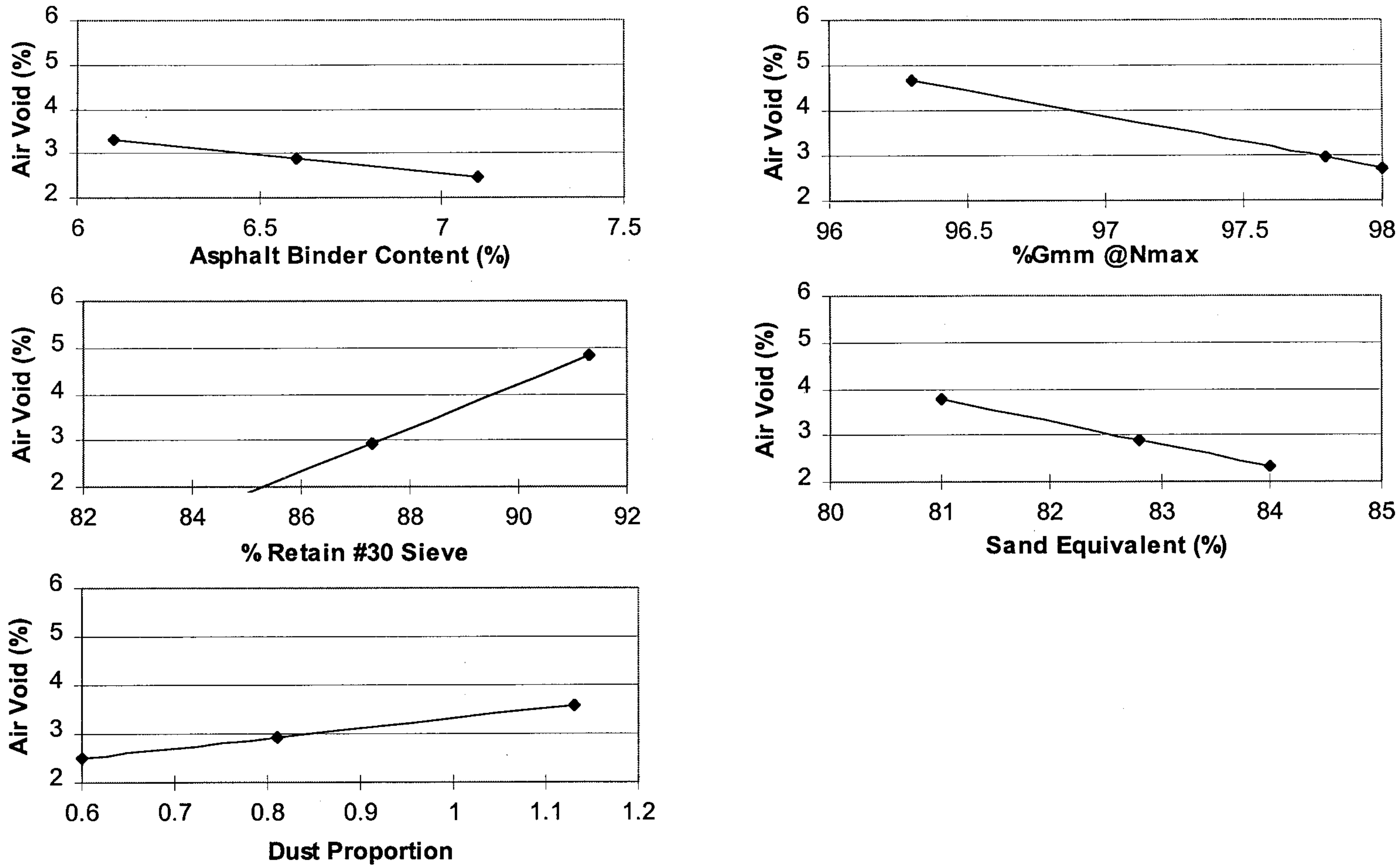

Figure 5.1 Sensitivity Analysis Results for Va of SM-1T (Change Order)

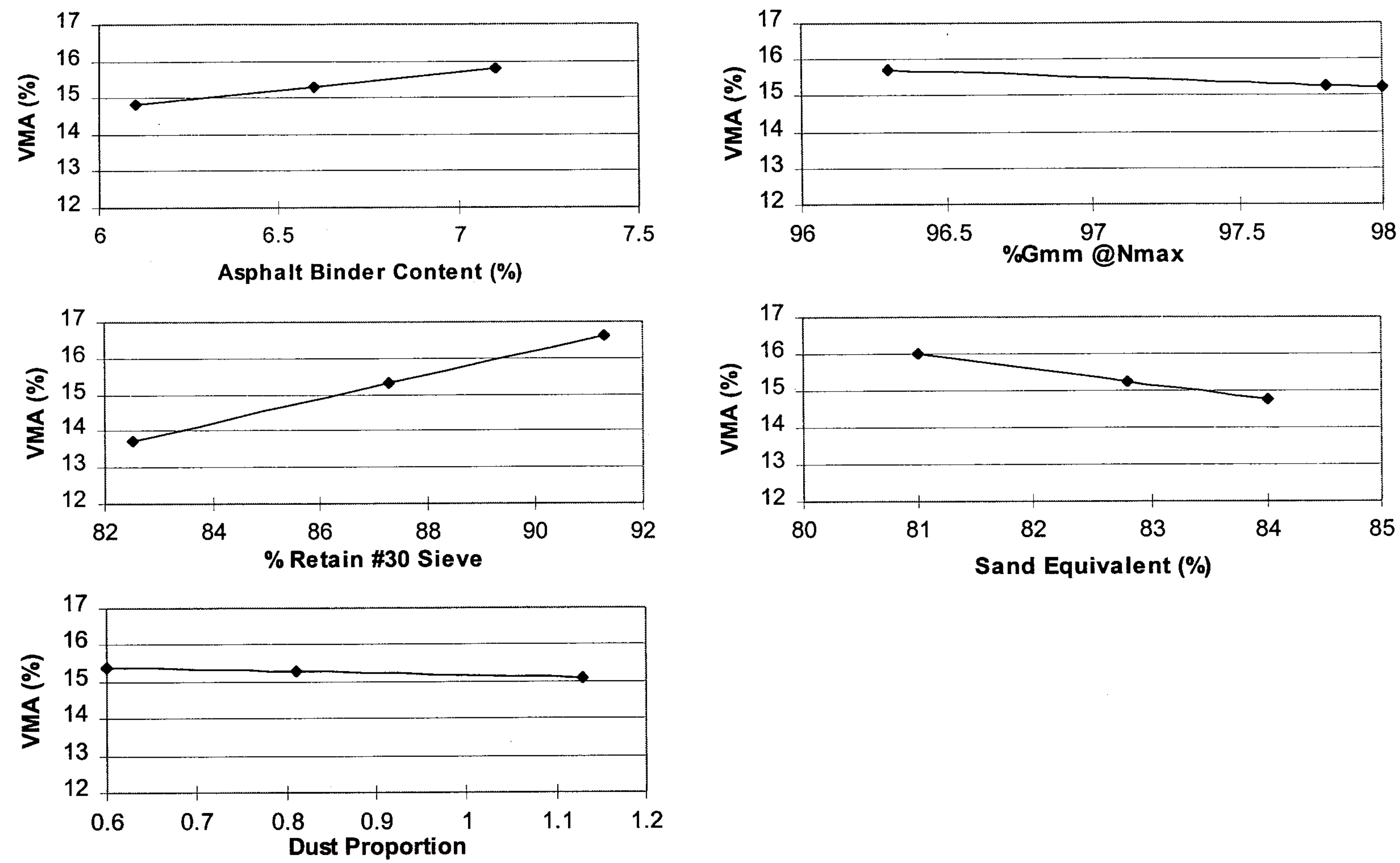

Figure 5.2 **Sensitivity Analysis Results for VMA of SM-1T (Change Order)**

increases VMA by about 1.5%. The KDOT requirement for VMA for the 9.5 mm (3/8 in.) mix on a single test is minimum 14% (= 15% -1%). To achieve this, at least 84% of the materials should be retained on the 0.6 mm (#30) sieve. However, KDOT currently requires at least 76% be retained on this sieve size. This may need further study. In fact, the 0.6 mm (#30) sieve seems to be a very critical sieve for the Superpave mixtures currently being produced in Kansas.

VMA also does not appear to be as sensitive to the changes in the binder content as conventional thinking would indicate. This again might be due to the higher binder contents (6.1 to 7.1%) used on these projects. The figure also shows that the VMA values are fairly insensitive to the dust proportion values, which is not unusual since the dust proportion was tightly controlled on all Kansas Superpave projects. Production was once suspended on the I-70 U.S. Asphalt project because of failure to control dust proportion.

5.6.2 SM-2A: 12.5 mm Nominal Maximum Size Mixture (Change Order)

Table 5.5 indicates that the air void at N_{design} for the 12.5 mm Superpave mixture is significantly affected by the asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, and percent material retained on the 0.6 mm (#30) sieve. The statistical information for the VMA correlation equation in Table 5.6 shows that the VMA correlates with the asphalt binder content, $\%G_{mm}@N_{min}$, and percent material retained on the 9.5 mm (3/8") sieve. Figure 5.3 shows that $\%G_{mm}@N_{min}$ significantly affects the air void-a five percent change in $\%G_{mm}@N_{min}$ will decrease the air void by 2%. Air void is not very sensitive to the changes in the other three factors: asphalt binder content, $\%G_{mm}@N_{max}$, and percent material retained on the 0.6 mm (#30) sieve. Figure 5.4 also shows that VMA is most sensitive to the changes in $\%G_{mm}@N_{min}$. A 5% change in $\%G_{mm}@N_{min}$ will decrease the VMA by 2%.

5.6.3 SM-2C: 19 mm Nominal Maximum Size Mixture without RAP (Change Order)

Table 5.9 indicates that the air void at N_{design} for the 19 mm Superpave mixture without recycled asphalt pavement (RAP) is significantly affected by $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percent material retained on the 12.5 mm (1/2") sieve and percent material retained on the 0.6 mm (#30) sieve. Table 5.10 shows that the VMA correlates with the $\%G_{mm}@N_{min}$ and dust proportion. Figure 5.5 shows that percent material retained on the 0.6 mm (#30) sieve significantly affects the air void. A 5% change in the percent of material retained on the 0.6 mm (#30) sieve will result in almost 3% air void decrease. Air void is not very sensitive to the changes in the other two factors: $\%G_{mm}@N_{min}$, and percent material retained on 12.5 mm (1/2") sieve. Figure 5.6 also shows that the VMA is very sensitive to the changes in both $\%G_{mm}@N_{min}$ and dust proportion. Higher values of these variables would significantly lower the VMA.

5.6.4 SR-2C: 19 mm Nominal Maximum Size Mixture with RAP (Change Order)

Table 5.13 indicates that the air voids at N_{design} for the 19 mm Superpave mixture with RAP is significantly affected by the $\%G_{mm}@N_{min}$, percent retained on the 0.6 mm (#30) sieve, and dust proportion. The interaction between the $\%G_{mm}@N_{min}$ and the percent of material retained on the 0.6 mm (#30) sieve is also significant. Table 5.14 indicates that the VMA is significantly affected by the asphalt binder content, $\%G_{mm}@N_{min}$, percent retained on the

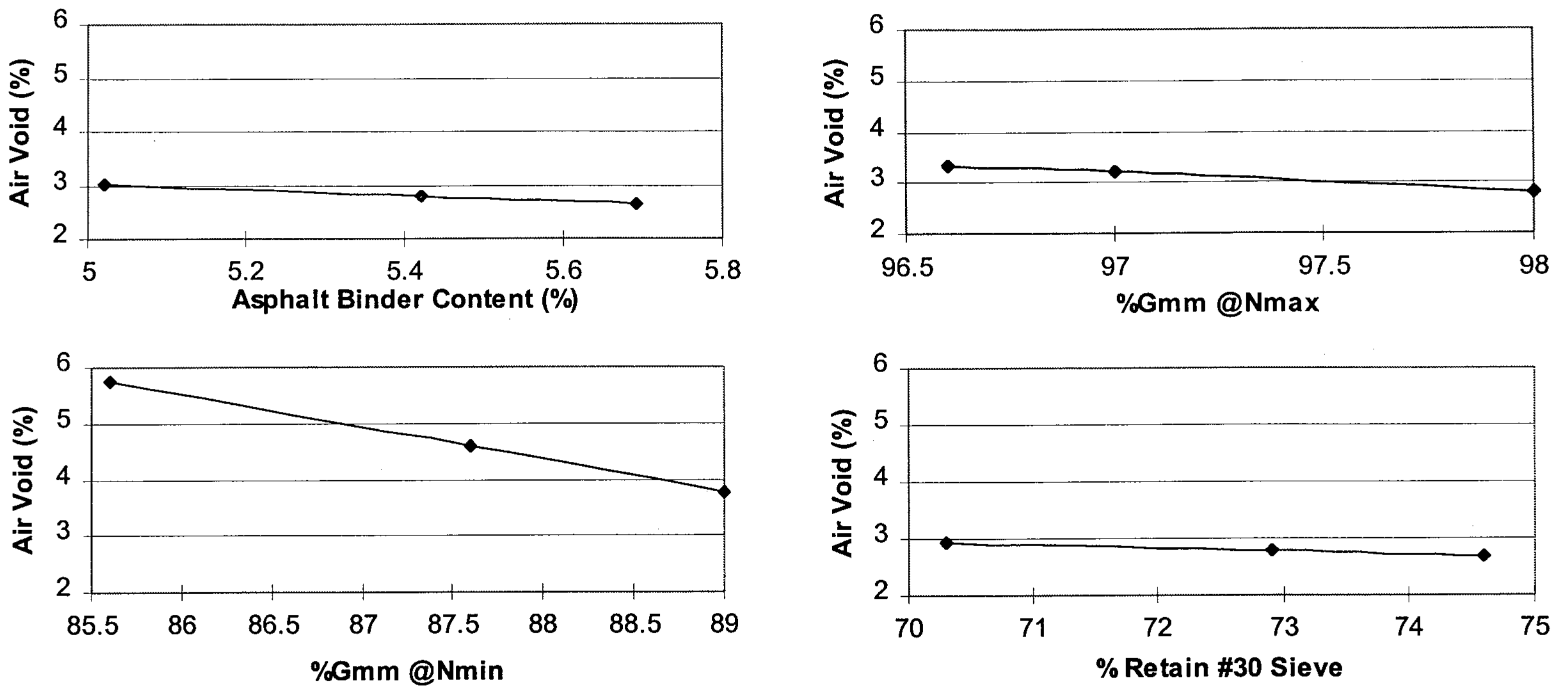

Figure 5.3 Sensitivity Analysis Results for Va of SM-2A (Change Order)

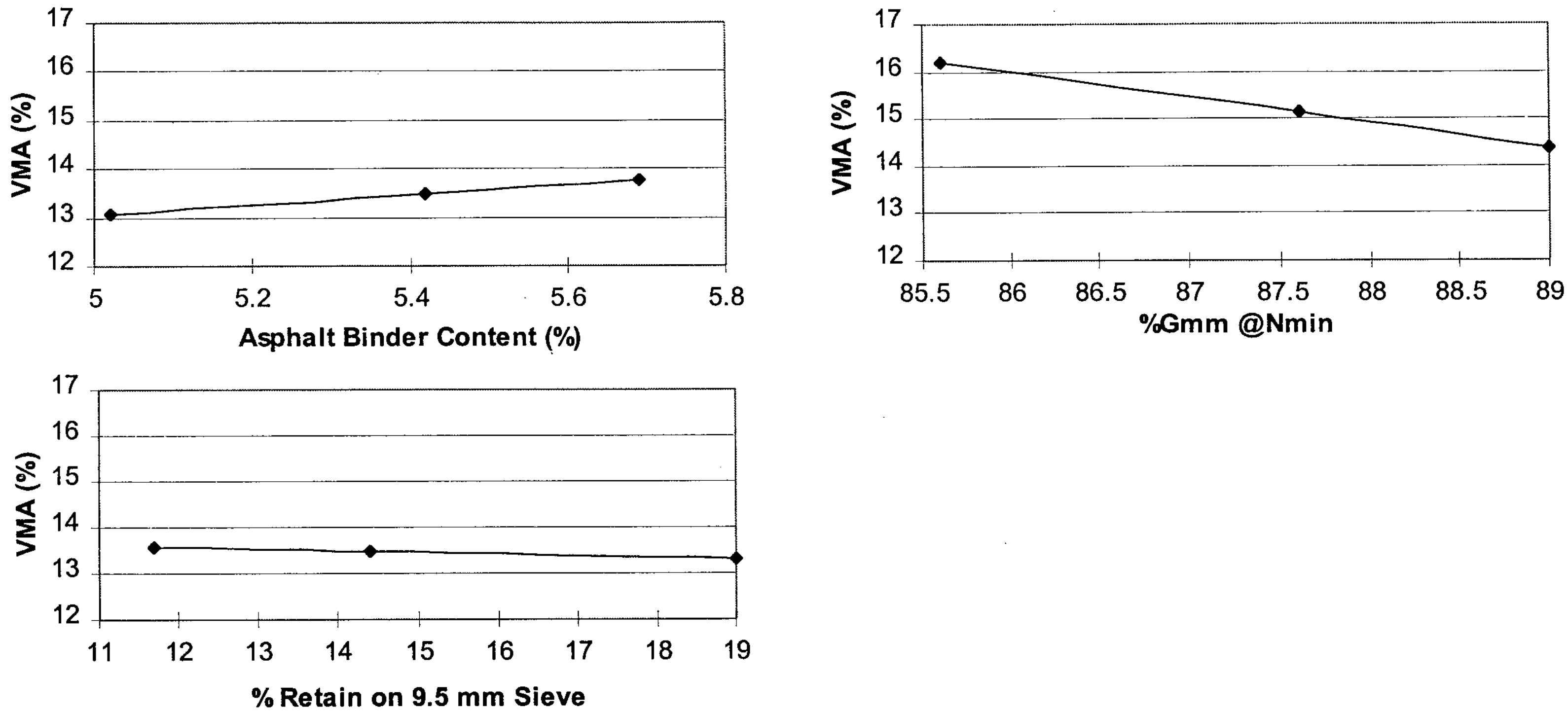

Figure 5.4 Sensitivity Analysis Results for VMA of SM-2A (Change Order)

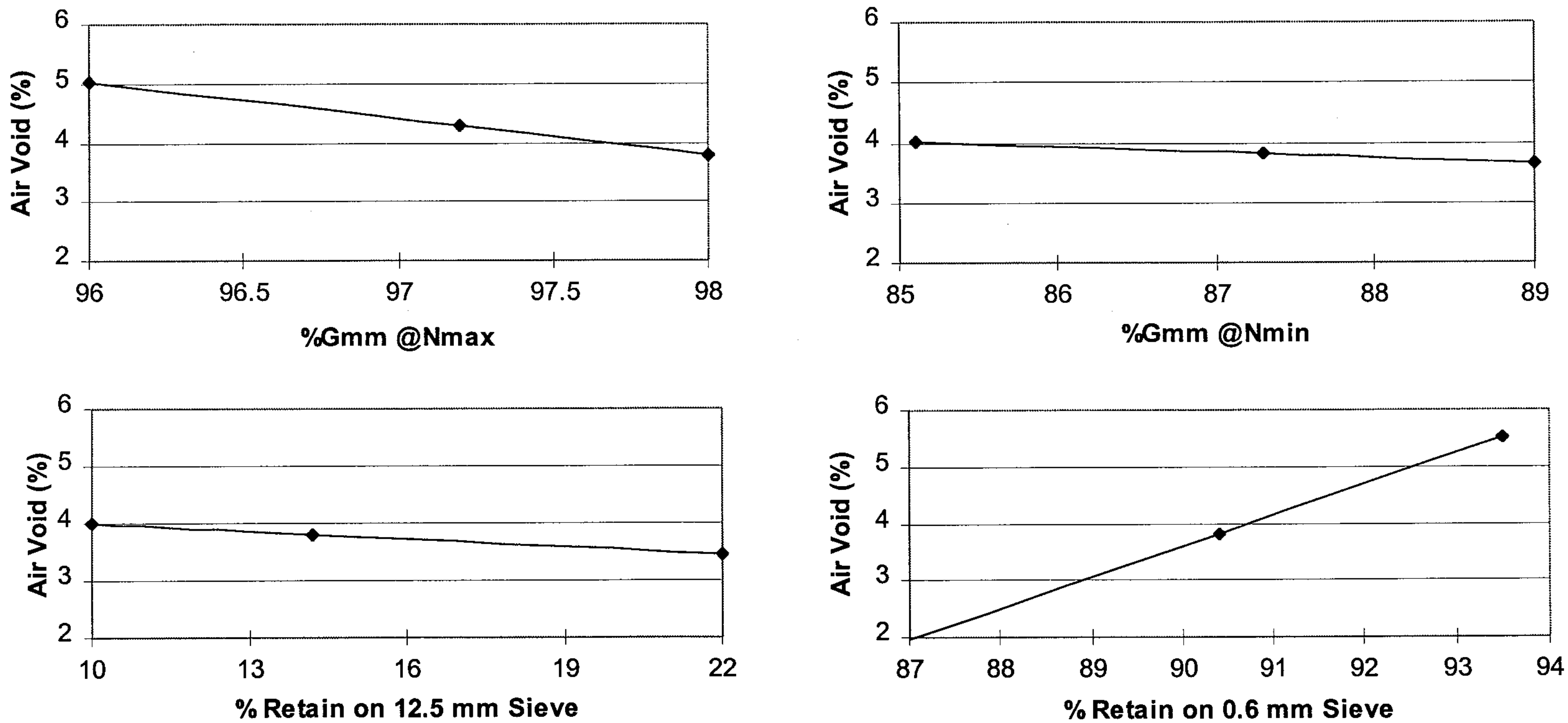

Figure 5.5 Sensitivity Analysis Results for Va of SM-2C (Change Order)

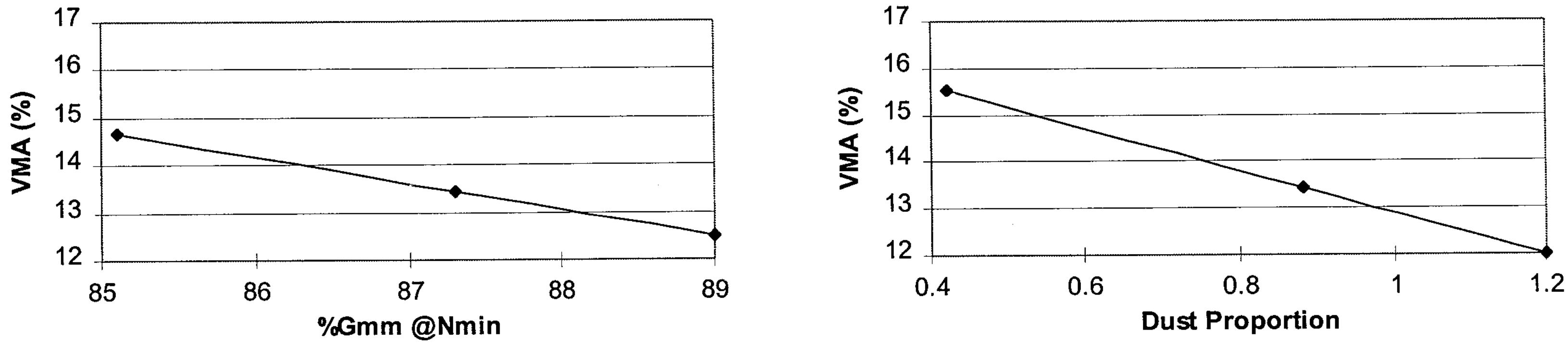

Figure 5.6 Sensitivity Analysis Results for VMA of SM-2C (Change Order)

0.6 mm (#30) sieve, Sand Equivalent value, and interaction between the $\%G_{mm}@N_{min}$ and the percent material retained on the 0.6 mm (#30) sieve. Figure 5.7 shows that air void is most sensitive to the changes in $\%G_{mm}@N_{min}$. From Figure 5.8, it appears that all factors affect the VMA equally if they are in the ranges required by the KDOT QC/QA program. It is interesting to note that all factors individually are positively correlated with the Va and VMA even though some coefficients in the equation are negative. This is due to the interaction terms in the equations, and it can be concluded that some factors will not affect the Va and VMA independently. This implies that controlling only one factor sometimes will not control the Va and VMA. The combination effects (interactions) could be dominant in controlling the Va and VMA.

5.6.5 SM-2C: 19 mm Nominal Maximum-Size Mixture without RAP (Let)

Table 5.17 indicates that the air void at N_{design} for the 19 mm virgin Superpave mixture is significantly affected by the asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percent of material retained on the 12.5 mm (1/2") sieve, percent of material retained on the 0.6 mm (#30) sieve and Sand Equivalent and some interactions. The statistical information for the VMA correlation equation in Table 5.18 shows that the VMA is correlated with the asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percent of material retained on the 12.5 mm (1/2") sieve, percent of material retained on the 0.6 mm (#30) sieve and dust proportion. The table indicates that the most dominant factor are $G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, and percent of material retained on the 0.6 mm (#30) sieve which is also supported by the plots in Figures 5.9 and 5.10. Air void is not very sensitive to the changes in three factors: asphalt binder

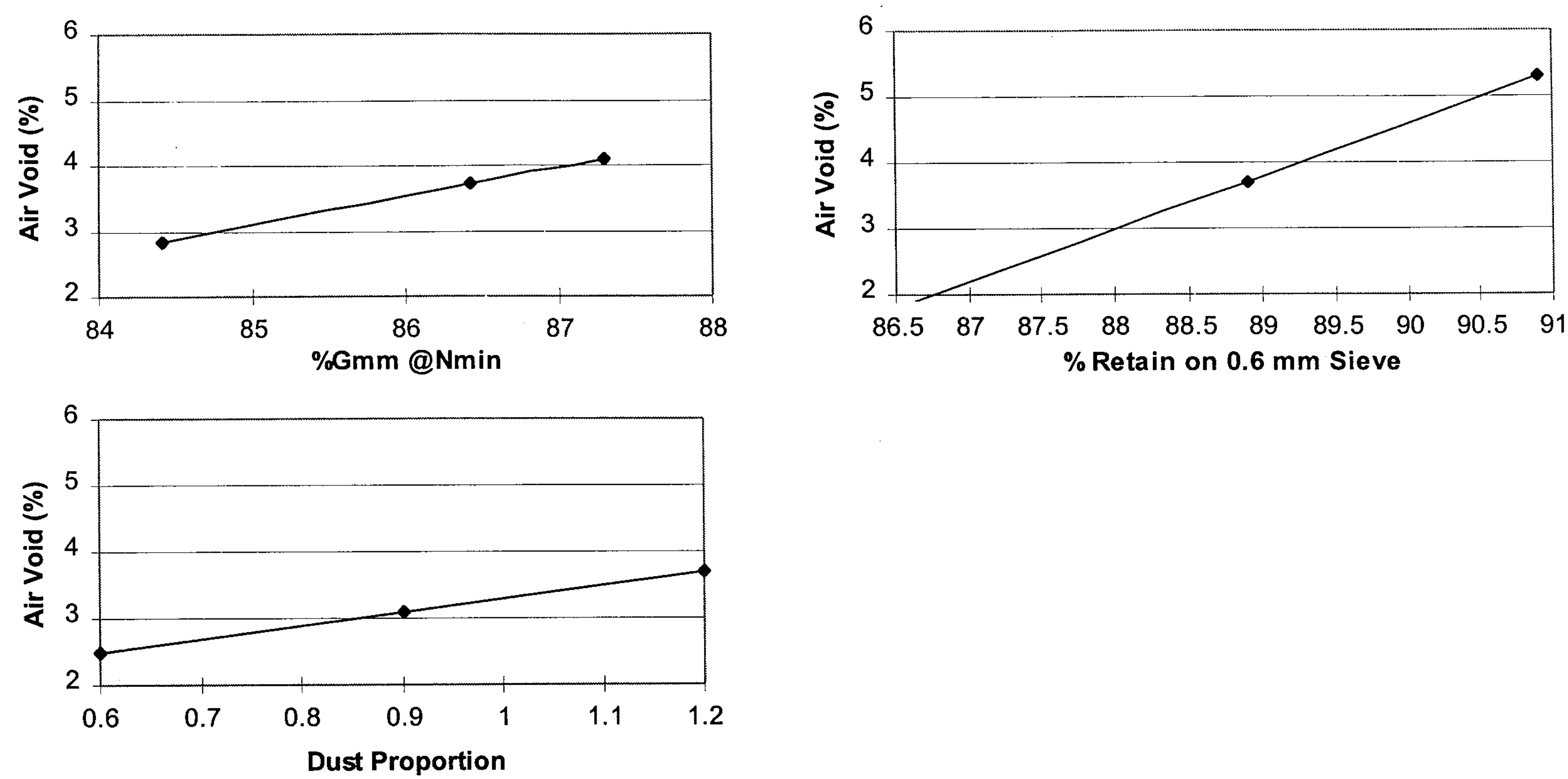

Figure 5.7 Sensitivity Analysis Results for Va of SR-2C (Change Order)

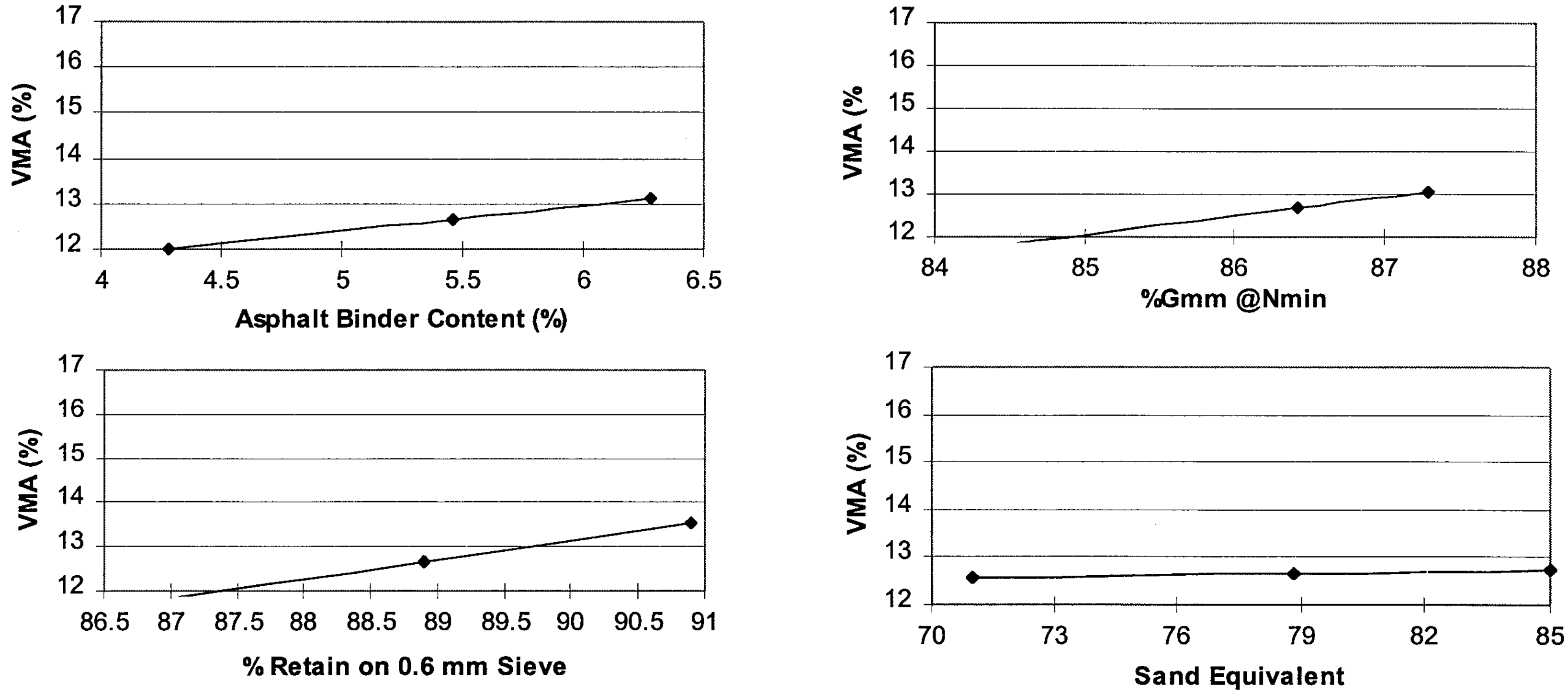

Figure 5.8 Sensitivity Analysis Results for VMA of SR-2C (Change Order)

content, percent of material retained on the 12.5 mm (1/2") sieve and sand equivalent. VMA is not very sensitive to the changes in percent of material retained on the 12.5 mm (1/2") sieve.

5.6.6 SR-2C: 19 mm Nominal Maximum-Size Mixture with RAP (Let)

Table 5.20 indicates that the air void at N_{design} for the 19 mm virgin Superpave mixture with RAP is significantly affected by the asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percent of material retained on the 0.6 mm (#30) sieve, sand equivalent and dust proportion. Table 5.21 shows that the VMA correlates with the same variables as for the air void at N_{design}, as well as, the interactions of all other variables and the dust proportion. Figure 5.11 indicates that the most dominant factors for air void are $\%G_{mm}@N_{max}$ and $\%G_{mm}@N_{min}$. Figure 5.12 shows that VMA is very sensitive to the changes in the asphalt binder content, $\%G_{mm}@N_{min}$ and percent of material retained on the 0.6 mm (#30) sieve. Air void is not sensitive to the changes in four factors: asphalt binder content, percent of material retained on the 0.6 mm (#30) sieve, sand equivalent and dust proportion.

5.6.7 Comparison between Let Projects and Change Order Projects

Table 5.23 summarizes the factors which significantly affect the air void of the 19 mm nominal maximum size mixtures with or without RAP. A number of common factors exist between the mixtures without RAP: $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percent of material retained on the 12.5 mm sieve, and percent of material retained on the 0.6 mm (#30) sieve. The common factors for the mixtures with RAP are: $\%G_{mm}@N_{min}$, percent of material retained

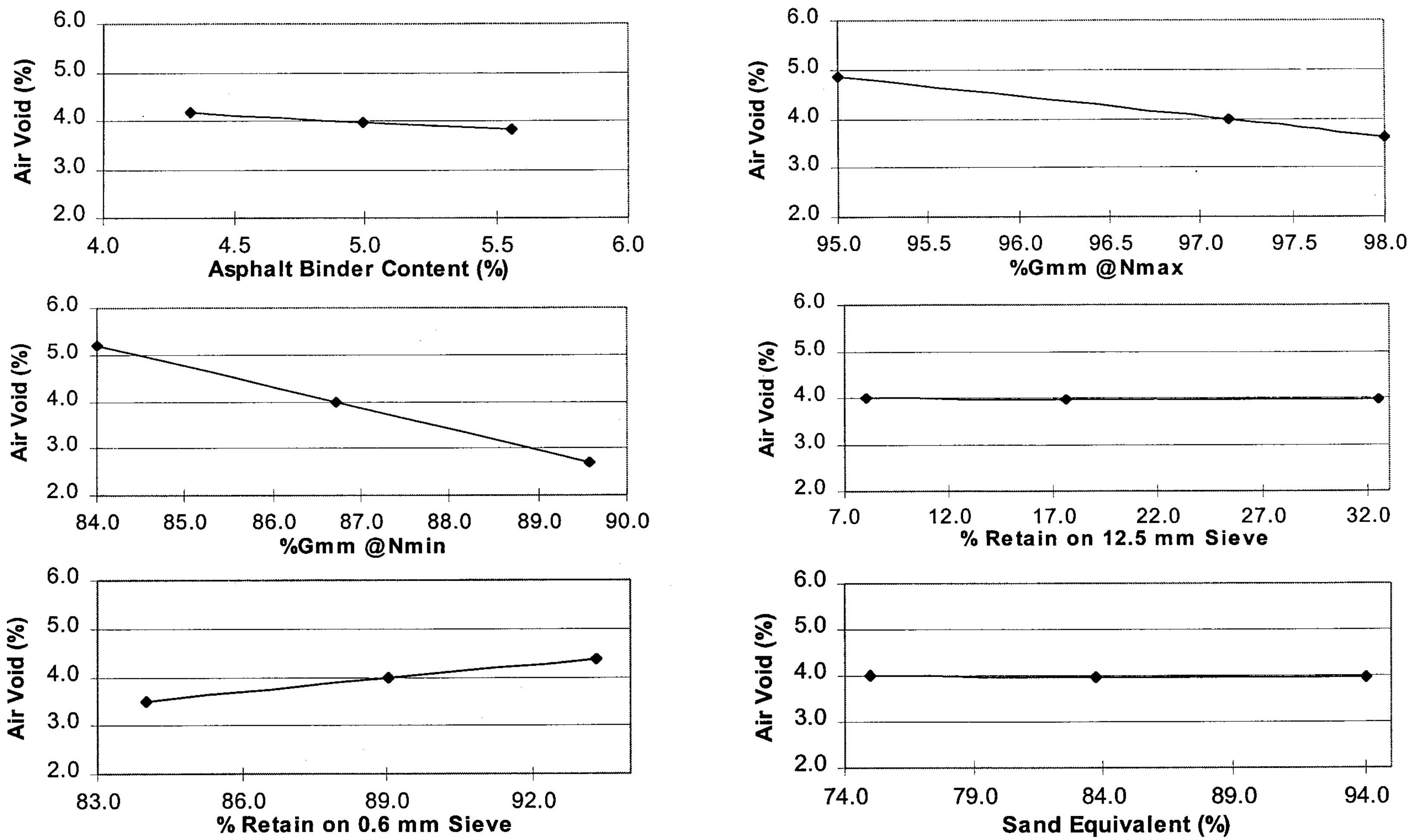

Figure 5.9 Sensitivity Analysis Results for Va of SM-2C (Let)

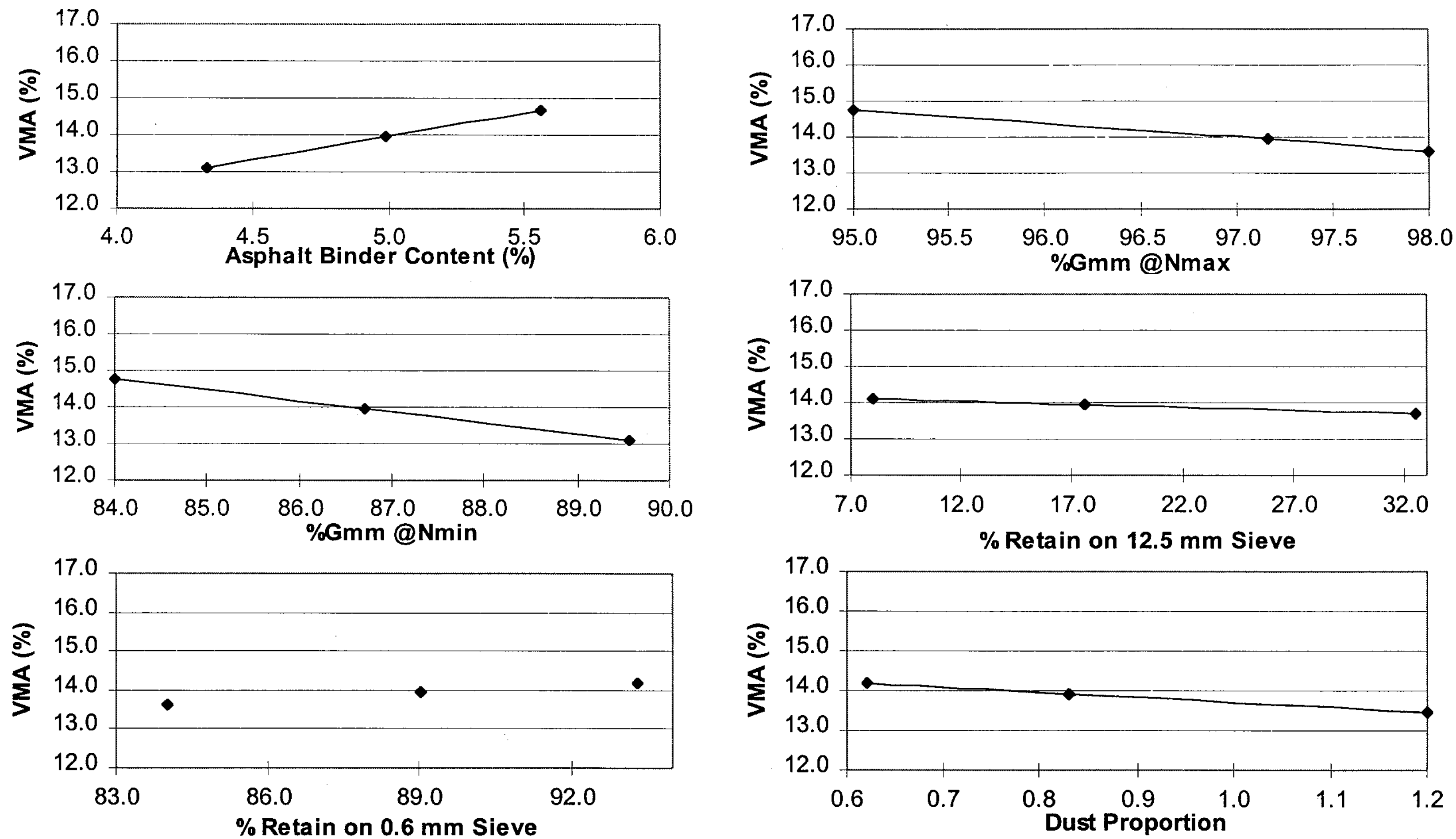

Figure 5.10 Sensitivity Analysis Results for VMA of SM-2C (Let)

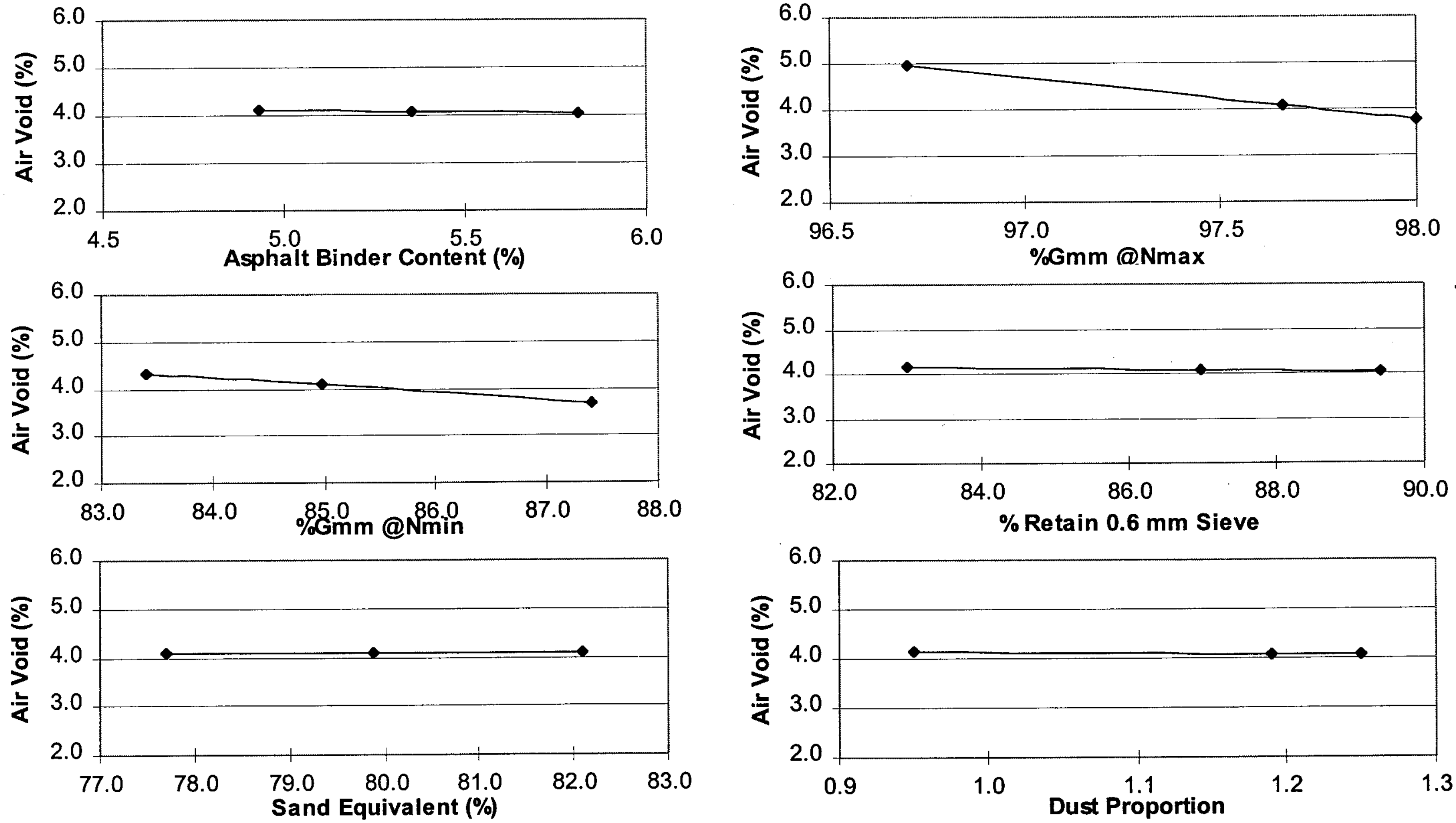

Figure 5.11 Sensitivity Analysis Results for Va of SR-2C (Let)

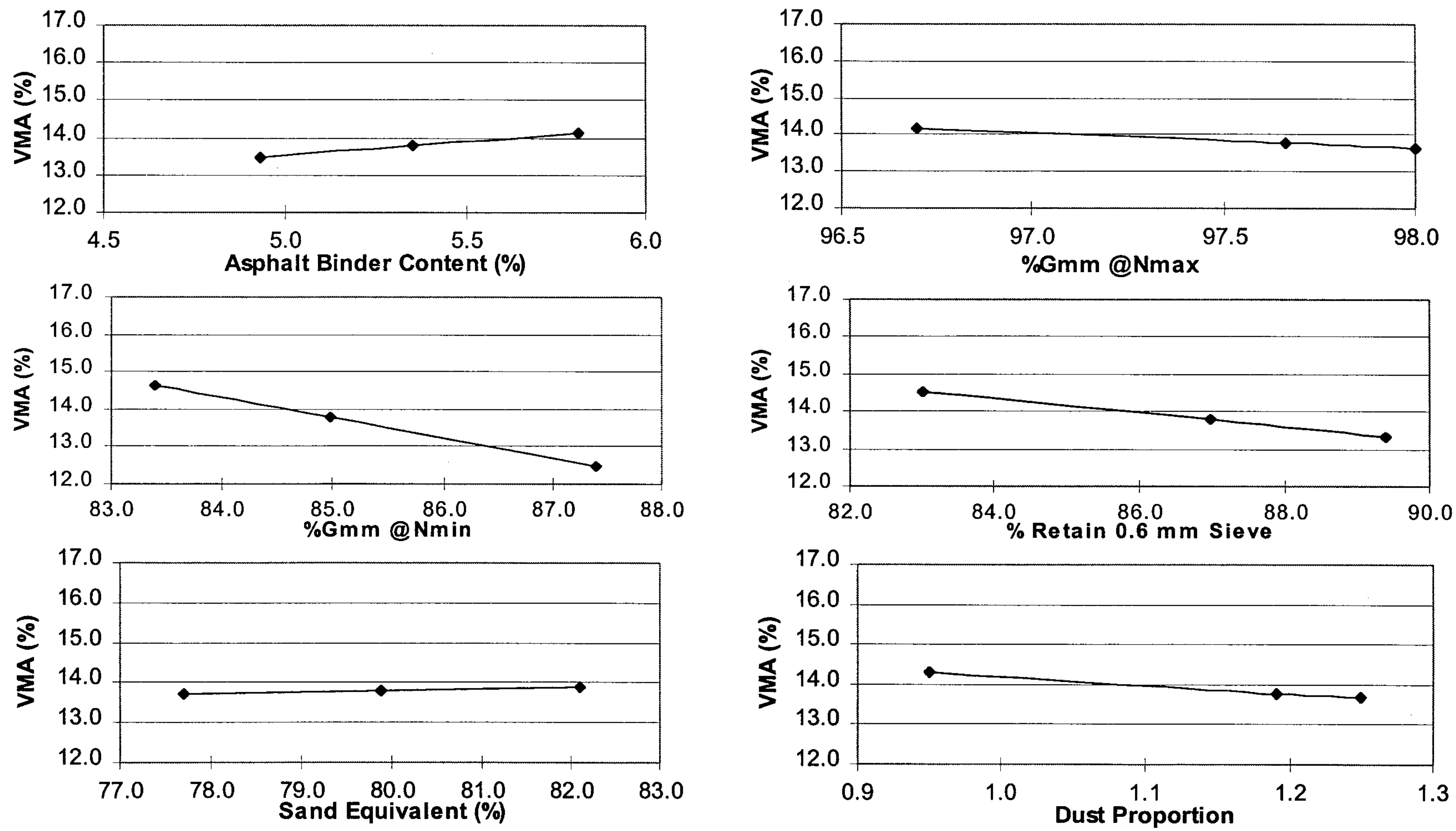

Figure 5.12 Sensitivity Analysis Results for VMA of SR-2C (Let)

on the 0.6 mm (#30) sieve, and dust proportion. For VMA of the 19 mm mixture without RAP, only $\%G_{mm}@N_{min}$, and dust proportion were the common factors. But for the mixtures with RAP, $\%G_{mm}@N_{min}$, percent of material retained on the 0.6 mm (#30) sieve, and sand equivalent appear in the predictive equations for mixtures under both change order and let contracts.

Table 5.24 Comparisons between Change Order Projects and Let Projects for Va

Factors	19 mm mixture without RAP		19 mm mixture with RAP	
	Change Order	Let	Change Order	Let
Pb		x		x
$\%G_{mm}@N_{max}$	x	x		x
$\%G_{mm}@N_{min}$	x	x	x	x
%Retained on 12.5 mm	x	x		
%Retained on 0.6 mm	x	x	x	x
CAA				
Sand Equivalent		x		x
Dust Proportion			x	x

Note: "x" means significant effect

Table 5.25 **Comparisons between Change Order Projects and Let Projects for VMA**

Factors	19 mm mixture without RAP		19 mm mixture with RAP	
	Change Order	Let	Change Order	Let
Pb		x	x	x
$\%G_{mm}@N_{max}$		x		x
$\%G_{mm}@N_{min}$	x	x	x	x
%Retained on 12.5 mm		x		
%Retained on 0.6 mm		x	x	x
CAA				
Sand Equivalent			x	x
Dust Proportion	x	x		x

Note: "x" means significant effect

6.0 MULTIPLE PROPERTY OPTIMIZATION

6.1 Background

Multiple property optimization (MPO) discussed here is an unconstrained optimization problem in the mathematical sense of maximization or minimization. The problem involves choosing values, in the feasible region, for the control variables $x_1,\cdots,x_n$, known as decision variables, so as to maximize a real-valued function f of those variables. Formally, the structure of this problem may be expressed as: *(Beavis et al. 1990)*

$$\max_{\{x_1,\cdots,x_n\}} f(x_1,\cdots,x_n) \tag{6.1}$$

where in the current research, $f(x_1,\cdots,x_n)$ is the total **goodness** of two properties: Va and VMA. The $x_1,\cdots,x_n$ are the variables used to obtain the prediction correlation equations for the Va and VMA, such as, asphalt binder content, $\%G_{mm}@N_{max}$, and so on.

6.2 Information Needed for MPO

A commercial software called Multiple Property Optimization was used in this study *(MPO 1991)*. The information below should be collected for the MPO analysis:

***1. Correlation Equations*:** These equations quantify how the independent variables affect the dependent variables. The dependent variables are the properties which are being optimized. The properties can be adjusted only indirectly by means of adjusting the independent variables. The analysis done by MPO will be only as good as the correlation equations on which it is based. Therefore, it is extremely important to obtain good correlation equations. The correlation equations used in this study were obtained from the MCA results as discussed in Chapter 5. Due to the fact that good correlation equations can be found for Va and VMA, but not for the in-place pavement density and TSR, it was decided that only those two properties will be used in the MPO analysis.

***2. Goodness Relationships*:** A goodness equation is a rating system that describes the various levels for the properties being optimized. It describes the target and specification limits for the properties and how much it hurts the goodness for being off target value. A rating system of zero to ten is usually used, where the most desirable level, or the target value, is given a rating of ten (10) and any undesirable region is given a rating of zero (0). Desirable regions between the target and the unacceptable regions are scaled accordingly.

***3. Levels of the Independent Variables*:** These are the levels of the independent variables studied. The minimum and the maximum are determined for each variable by referring to the data set used to develop the correlation equations. In addition, several intermediate levels are selected for the MPO analysis.

6.3 MPO Results

Multiple Property Optimization was performed for only two mixtures from the let projects because some projects built under the change order did not have optimum mix design. The objective of the MPO analysis was to find a combination of independent variable levels to achieve the maximum of total goodness, or in other words, to obtain Va and VMA simultaneously as close to their target values as possible.

Two mixtures were analyzed: SM-2C, 19 mm nominal maximum size mixture without RAP and SR-2C, 19 mm nominal maximum size mixture with RAP. The correlation equations for the two mixtures used in MPO have been shown in Tables 5.17 and 5.18, and Tables 5.20 and 5.21, respectively. The Va and VMA of SM-2C correlate with the asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percentage of material retained 12.5 mm (½ in.), percentage of material retained on the 0.60 mm (#30) sieve, sand equivalent, and dust proportion. The Va and VMA of SR-2C correlate with asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percentage of material retained on the 0.60 mm (#30) sieve, sand equivalent, and dust proportion.

Based on KDOT QC/QA specifications for the 19 mm nominal maximum size mixtures, a target value of 4% was used for Va, and it was determined that a Va above 6% or below 2% is unacceptable. These requirements were converted to a rating system ranging from 0 (unacceptable) to 10 (target) as shown in Figure 6.1. The target value for VMA of SM-2C or SR-2C is 13% or greater. VMA below 12% is unacceptable. The rating system for VMA is presented in Figure 6.2. The levels of the independent variables are the maximum, minimum and median of each data set.

The total goodness is calculated using the arithmetic sum method as follows:

$$G_{Total} = W_1 G_1 + W_2 G_2 + \ldots + W_n G_n \tag{6.1}$$

where: G = goodness,

W = weighting factor, and

n = number of properties being optimized.

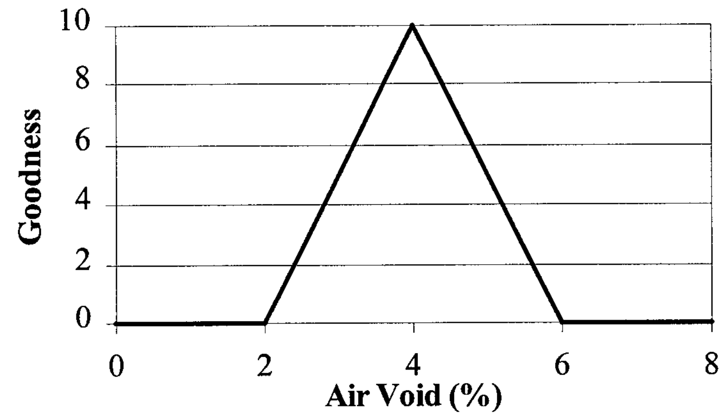

Figure 6.1 **Rating System for Va**

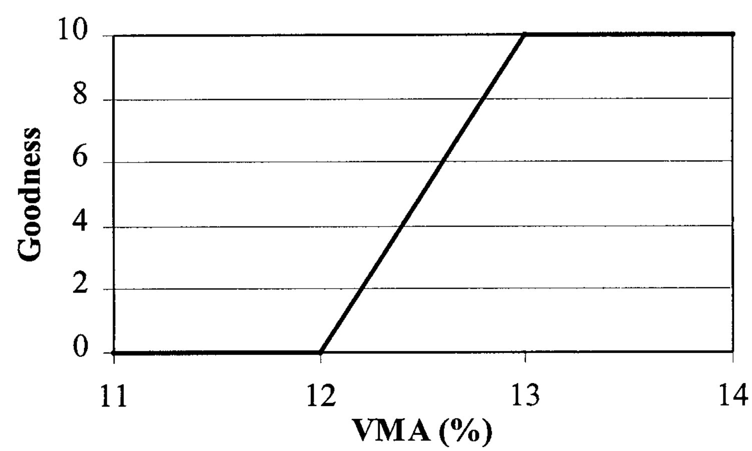

Figure 6.2 **Rating System for VMA**

In our problem, n is equal to two. The default weighting factor for any goodness equation is one (1). If all the weighting factors are one, then every equation holds equal importance in the total goodness calculation. The weighting factor can be changed according to the importance of the evaluated goodness equation compared to others.

The calculation steps are summarized as below:

1. Enter each combination of the process variable levels into the correlation equations and compute the resulting properties;
2. For each resulting property, determine the corresponding goodness; and
3. Calculate the G_{Total} using the Equation (6.1).

The optimum combination is the combination of the variables that gives the highest G_{Total}.

The optimization results are shown in Tables 6.1 and 6.2 for SM-2C and SR-2C, respectively. Since all the values of percent goodness are close to 100%, the best combination should be based on engineering judgement. The most desirable volumetric properties are highlighted in Table 6.1 and 6.2, respectively. In both cases, the mixtures have Va close to or equal to 4% which is the target value, and VMA above 13%, but not higher than 14%, and dust proportion is equal to 0.9%. The other factors are in reasonable ranges.

6.4 Comparisons between KDOT Specified and Suggested Working Ranges

Comparison between the KDOT specified and the suggested working ranges from the MPO analysis are shown in Tables 6.3 and 6.4. It is noted that the suggested working range for

Table 6.1 MPO Results of SM-2C (Let)

G_{Total}	Percent Goodness	Va (%)	VMA (%)	Pb (%)	$\%G_{mm}$ @N_{max}	$\%G_{mm}$ @N_{min}	%Retained on 12.5 mm	%Retained on 0.6 mm	SE (%)	DP
19.98	99.90	4.00	13.06	4.5	98	84	16	94	84	0.9
19.98	99.90	4.00	13.45	4.5	98	84	16	94	84	0.6
19.93	99.66	4.01	13.09	4.5	98	89	10	94	92	0.6
19.92	99.62	4.02	13.16	4.5	98	84	10	94	84	0.9
19.92	99.62	4.02	13.55	4.5	98	84	10	94	84	0.6
19.92	99.60	4.00	12.99	4.5	98	89	16	94	92	0.6
19.91	99.56	4.02	15.38	5.5	94	89	30	89	76	1.2
19.91	99.56	4.02	15.77	5.5	94	89	30	89	76	0.9
19.91	99.56	4.02	16.16	5.5	94	89	30	89	76	0.6
19.89	99.43	3.98	13.23	4.5	98	84	30	94	84	0.6
19.84	99.18	3.97	13.31	5.5	98	84	10	94	76	0.6
19.78	98.90	4.04	15.60	5.5	94	89	16	89	76	1.2
19.78	98.90	4.04	15.99	5.5	94	89	16	89	76	0.9
19.78	98.90	4.04	16.38	5.5	94	89	16	89	76	0.6
19.78	98.90	3.96	13.21	5.5	98	84	16	94	76	0.6

Table 6.2 MPO Results of SR-2C (Let)

G_{Total}	Percent Goodness	Va (%)	VMA (%)	Pb (%)	$\%G_{mm}$ $@N_{max}$	$\%G_{mm}$ $@N_{min}$	%Retained on 0.6 mm	SE (%)	DP
19.99	99.93	4.00	15.52	5.8	98	85	83	82	0.9
19.97	99.85	4.01	15.16	5.8	98	85	86	80	0.6
19.96	99.81	4.01	15.22	5.3	97	83	86	76	0.6
19.95	99.76	3.99	13.19	5.8	97	88	83	80	1.2
19.94	99.71	4.01	13.44	5.8	97	88	83	76	1.2
19.92	99.62	3.98	13.65	5.8	98	88	86	76	0.9
19.90	99.50	3.98	13.07	5.8	97	88	83	82	1.2
19.89	99.47	4.02	13.02	5.3	97	88	86	76	1.2
19.82	99.09	4.04	13.69	5.8	98	88	83	76	0.9
19.80	98.99	3.96	13.40	5.8	97	88	86	76	1.2
19.76	98.80	3.95	13.31	5.3	98	88	83	76	0.9
19.75	98.77	3.95	14.67	5.8	98	85	86	82	0.9
19.75	98.75	3.95	14.94	5.3	98	85	86	82	0.6
19.72	98.58	4.06	15.12	4.8	97	83	90	80	0.6

asphalt binder content from the MPO analysis is ± 0.5%, which is 67% larger than the KDOT specified range of ± 0.3%. It may indicate that KDOT specifications for the asphalt binder content may be too restrictive to keep the Superpave mixture quality at the desirable level in terms of Va and VMA. Further study is suggested to focus on this subject. For some mixture properties such as $\%G_{mm}@N_{ini}$, $\%G_{mm}@N_{max}$, aggregate gradation, and sand equivalent, the KDOT specifications only have one required limit for each property, either maximum or minimum. According to the MPO results (Tables 6.3 and 6.4), these limits appear to be reasonable to control the quality of the Superpave mixtures. The dust proportion has similar limits in both suggested and current KDOT-specified working ranges.

Table 6.3 Comparison of Current KDOT Specified and Suggested Working Ranges for SM-2C (Let)

Volumetric Property	KDOT Specification Working Range (four-point moving average)	Suggested Range from MPO
Pb	± 0.3%	± 0.5%
$\%G_{mm}@N_{ini}$	89% max	84%-89%
$\%G_{mm}@N_{max}$	98% max	94%-98%
%Retained on 12.5 mm	10% min	16%-30%
%Retained on 0.6 mm	83% min	89%-94%
SE	40% min	76%-92%
DP	0.6-1.2	0.6-1.2

Table 6.4 Comparison of Current KDOT Specified and Suggested Working Ranges for SR-2C (Let)

Volumetric Property	KDOT Specification Working Range (four-point moving average)	Suggested Range from MPO
Pb	± 0.3%	± 0.5%
$\%G_{mm}@N_{ini}$	89% max	83%-88%
$\%G_{mm}@N_{max}$	98% max	97%-98%
%Retain on 0.6 mm	83% min	83%-90%
SE	40% min	76%-82%
DP	0.6 -1.2	0.6 -1.2

7.0 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

Based on the analysis of the results from this study, the following conclusions may be drawn:

1. A four-step modeling framework was used to study the relationships among 19 Superpave volumetric properties monitored by the KDOT QC/QC program. Principal component analysis was used to transform a set of correlated variables into a smaller set of uncorrelated variables. Multiple correlation analysis was performed to obtain a series of linear relationships between the predictor variables and the response variables. Sensitivity analysis was done to quantify the effects of changes in predictor variables on the response variables. Finally, multiple property optimization was carried out to achieve the most desirable output properties by adjusting the levels of independent variables.

2. PCA resulted in the following subgroups of the predictor variables for the Superpave mixtures in this study:

   Group 1: percent retained on the 2.36 mm (#8) sieve, percent retained on the 1.18 mm (#16) sieve, percent retained on the 0.6 mm (#30) sieve, and percent retained on the 0.3 mm (#50) sieve;
   Group 2: percent retained on the 0.075 mm (#200) sieve, fine aggregate angularity, and dust proportion;
   Group 3: percent retained on the 19 mm (3/4") sieve, percent retained on the 12.5 mm (1/2") sieve, and percent retained on the 9.5 mm (3/8") sieve;
   Group 4: sand equivalent;
   Group 5: asphalt binder content;
   Group 6: $\%G_{mm}$ @ N_{max};
   Group 7: $\%G_{mm}$ @ N_{min} ; and
   Group 8: coarse aggregate angularity.

The variables within a subgroup are highly correlated among themselves, and the variables between the subgroups are not significantly correlated. This reduces the 15-dimension data set to a 8-dimension, uncorrelated subgroup.

3 Good predictive equations were obtained using the predictors isolated in this study for the Va and VMA. It appears that the volumetric and aggregate properties are adequate in estimating Va and VMA.

4 No statistically significant equations were obtained for the in-place pavement density. This was somewhat expected since in-place pavement density also depends upon compactive effort, environmental factors: such as temperature and wind, etc., in addition to, the mixture constituents.

5 The regression equations for TSR had R^2 values of 0.52 for the smaller-size mixtures and 0.76 to 0.80 for the large-size mixtures. The difference in R^2 value may imply that volumetric properties have causative, not decisive, effects on the TSR. The moisture sensitivity of the Superpave mixtures may be more related to the properties of asphalt binder rather than to the asphalt binder content and other factors.

6 The coarse aggregate angularity does not appear in any predictive equations presumably due to the fact that all coarse aggregates used on Superpave projects in Kansas were entirely crushed materials.

7 For the 9.5 mm nominal maximum size mixture, the asphalt binder content, $\%G_{mm}$ at N_{max}, percentage of material retained on the 0.6 mm (#30) sieve, sand equivalent, dust proportion and the interaction between the sand equivalent and percentage of material retained on the 0.6 mm (#30) sieve, significantly affect the Va and VMA.

For VMA, the interaction between the $\%G_{mm}$ at N_{max} and the percentage of material retained on the 0.6 mm (#30) sieve is also significant.

8 For the 12.5 mm nominal maximum size mixture, Va is significantly affected by the asphalt binder content, $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, and percentage of material retained on the 0.6 mm (#30) sieve. The VMA correlates with the asphalt binder content, $\%G_{mm}@N_{min}$, and percentage of material retained on the 9.5 mm (3/8") sieve.

9 For the 19 mm nominal maximum size mixture, Va is significantly affected by $\%G_{mm}@N_{max}$, $\%G_{mm}@N_{min}$, percentage of material retained on the 0.6 mm (#30) sieve, VMA correlates well with the asphalt binder content, $\%G_{mm}@N_{min}$, percentage of material retained on the 0.6 mm (#30) sieve and dust proportion.

10 Multiple Property Optimization results show that the most desirable 19 mm nominal maximum size mixture is the one with air void close to or equal to 4%, and VMA above 13%, but not higher than 14%, dust proportion equal to 0.9, and other properties in the ranges specified by the KDOT QC/QA specification.

7.2 Recommendations

1 The major drawback of this study was limited data. The addition of more projects and more complete and better quality data on current let projects would significantly increase the statistical certainty of the results.

2 Since no reliable correlation equations were found for the in-place pavement density and TSR, further investigation of other key variables that might affect these two variables is suggested.

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APPENDIX A: SAS Code, Log File, and Output File of PCA

Statistical Analysis System (SAS) Codes

```
options linesize=66 pagesize=60 NODATE;
TITLE 'SUPERPAVE PROJECT-PCA ANALYSIS---For All Raw Data';
DATA TOTAL;
infile 'total3.prn';
INPUT VA VMA DENSITY PB NMAX NMIN R34 R12
        R38 R8 R16 R30 R50 R200 TSR SE FAA
        CAA DP;
CARDS;

PROC PRINT;
RUN;

PROC PRINCOMP DATA=TOTAL OUT=PCSCORES;
VAR  VA VMA DENSITY PB NMAX NMIN R34 R12
      R38 R8 R16 R30 R50 R200 TSR SE FAA
      CAA DP;
TITLE2 'PC ANALYSIS IS ON ALL RAW DATA SET';
RUN;

PROC PRINT DATA=PCSCORES;
VAR PRIN1-PRIN4;
TITLE2 'VALUES OF THE FIRST 4  PRINCIPAL COMPONENT SCORES';
RUN;
```

The SAS System: Log File

```
NOTE: Copyright (c) 1989-1996 by SAS Institute Inc., Cary, NC, USA.
NOTE: SAS (r) Proprietary Software Release 6.12  TS020
    Licensed to KANSAS STATE UNIVERSITY, Site 0003010005.

This message is contained in the SAS news file, and is presented upon
initialization.  Edit the files "news" in the "misc/base" directory to
display site-specific news and information in the program log.
The command line option "-nonews" will prevent this display.

NOTE: AUTOEXEC processing beginning; file is /usr/local/lic/sas612/autoexec.sas.

NOTE: SAS initialization used:
    real time       1.300 seconds
    cpu time        0.453 seconds

NOTE: AUTOEXEC processing completed.

1       options linesize=66 pagesize=60 NODATE;
2       TITLE 'SUPERPAVE PROJECT-PCA ANALYSIS---For All Raw
Data';
3       DATA TOTAL;
4       infile 'total3.prn';
5       INPUT VA VMA DENSITY PB NMAX NMIN R34 R12
6               R38 R8 R16 R30 R50 R200 TSR SE FAA
7               CAA DP;
8       CARDS;

NOTE: The infile 'total3.prn' is:
    File Name=/home/e/jch8828/superpave/total3.prn,
    Owner Name=jch8828,Group Name=other,
    Access Permission=rw-r--r--,
    File Size (bytes)=163779

NOTE: 709 records were read from the infile 'total3.prn'.
    The minimum record length was 230.
    The maximum record length was 230.
NOTE: The data set WORK.TOTAL has 709 observations and 19
    variables.
NOTE: DATA statement used:
    real time       0.880 seconds
    cpu time        0.401 seconds
```

```
PROC PRINT;
RUN;

NOTE: The PROCEDURE PRINT printed pages 1-28.
NOTE: PROCEDURE PRINT used:
    real time          0.890 seconds
    cpu time           0.570 seconds


PROC PRINCOMP DATA=TOTAL OUT=PCSCORES;
VAR  VA VMA DENSITY PB NMAX NMIN R34 R12
     R38 R8 R16 R30 R50 R200 TSR SE FAA
     CAA DP;
TITLE2 'PC ANALYSIS IS ON ALL RAW DATA SET';
RUN;

WARNING: 502 of 709 observations in data set WORK.TOTAL omitted
      due to missing values.
NOTE: The data set WORK.PCSCORES has 709 observations and 38
    variables.
NOTE: The PROCEDURE PRINCOMP printed pages 29-34.
NOTE: PROCEDURE PRINCOMP used:
    real time          0.580 seconds
    cpu time           0.225 seconds


PROC PRINT DATA=PCSCORES;
VAR PRIN1-PRIN4;
TITLE2 'VALUES OF THE FIRST 4  PRINCIPAL COMPONENT
SCORES';
RUN;

NOTE: The PROCEDURE PRINT printed pages 35-47.
NOTE: PROCEDURE PRINT used:
    real time          0.090 seconds
    cpu time           0.078 seconds

NOTE: The SAS System used:
    real time          4.040 seconds
    cpu time           1.796 seconds

NOTE: SAS Institute Inc., SAS Campus Drive, Cary, NC USA
    27513-2414
```

The SAS System: Output File

SUPERPAVE PROJECT-PCA ANALYSIS---For All Raw Data 29
PC ANALYSIS IS ON ALL RAW DATA SET

Principal Component Analysis

207 Observations
19 Variables

Simple Statistics

	VA	VMA	DENSITY	PB
Mean	3.905990338	14.46352657	92.35763285	5.204927536
StD	0.771524062	8.92509126	1.36410919	0.275451738

	NMAX	NMIN	R34	R12
Mean	97.48927536	86.43405797	1.210144928	15.82850242
StD	0.90713887	1.96134810	1.207839875	5.56763438

	R38	R8	R16	R30
Mean	28.08309179	70.06859903	79.80724638	86.03188406
StD	7.67792537	8.12683613	6.68695990	5.27725913

	R50	R200	TSR	SE
Mean	90.40917874	95.51429952	98.12748792	80.15555556
StD	3.53077494	0.89639102	8.80610553	5.73446873

	FAA	CAA	DP
Mean	45.06328502	96.42657005	1.000241546
StD	1.26738582	4.74737734	0.189707080

Correlation Matrix

	VA	VMA	DENSITY	PB	NMAX
VA	1.0000	0.0358	0.2321	-.4461	-.6254
VMA	0.0358	1.0000	0.0652	-.0486	-.0157
DENSITY	0.2321	0.0652	1.0000	-.4332	-.1730
PB	-.4461	-.0486	-.4332	1.0000	0.4466
NMAX	-.6254	-.0157	-.1730	0.4466	1.0000
NMIN	-.7237	-.0394	-.1132	0.0572	0.2814
R34	0.2597	0.1101	0.4361	-.6005	-.2665
R12	0.3094	-.0009	0.2676	-.4652	-.0984
R38	0.4177	0.0126	0.3855	-.5397	-.1882
R8	0.6252	0.0825	0.4615	-.4372	-.3133
R16	0.6019	0.0546	0.4661	-.4155	-.2946
R30	0.5683	0.0314	0.4839	-.4512	-.2730
R50	0.5121	0.0068	0.4581	-.4583	-.2406
R200	0.2976	0.0581	0.5524	-.6723	-.2838
SE	0.3088	0.0185	0.4079	-.4530	-.1745
FAA	0.0652	-.0427	-.4020	0.5302	0.1546
CAA	-.1785	-.1051	-.4443	0.4733	0.3046
DP	-.1484	-.0959	-.5248	0.5090	0.1743

	NMIN	R34	R12	R38	R8
VA	-.72 37	0.2597	0.3094	0.4177	0.6252
VMA	-.0394	0.1101	-.0009	0.0126	0.0825
DENSITY	-.1132	0.4361	0.2676	0.3855	0.4615
PB	0.0572	-.6005	-.4652	-.5397	-.4372
NMAX	0.2814	-.2665	-.0984	-.1882	-.3133
NMIN	1.0000	-.0386	-.3012	-.4113	-.7888
R34	-.0386	1.0000	0.5394	0.6048	0.4438
R12	-.3012	0.5394	1.0000	0.9396	0.5125
R38	-.4113	0.6048	0.9396	1.0000	0.6932
R8	-.7888	0.4438	0.5125	0.6932	1.0000
R16	-.7640	0.4665	0.5792	0.7469	0.9841
R30	-.6663	0.5353	0.6995	0.8409	0.9254
R50	-.5722	0.5598	0.7605	0.8778	0.8490
R200	0.1159	0.6525	0.4196	0.5252	0.3900
SE	-.2541	0.5501	0.7586	0.8029	0.5655
FAA	-.4970	-.5692	-.3070	-.3462	-.0009
CAA	0.0068	-.3762	0.2134	0.0173	-.4005
DP	-.2159	-.5521	-.2938	-.3964	-.2757

Correlation Matrix

	R16	R30	R50	R200	TSR
VA	0.6019	0.5683	0.5121	0.2976	0.1907
VMA	0.0546	0.0314	0.0068	0.0581	0.0217
DENSITY	0.4661	0.4839	0.4581	0.5524	0.2949
PB	-.4155	-.4512	-.4583	-.6723	-.3774
NMAX	-.2946	-.2730	-.2406	-.2838	-.1387
NMIN	-.7640	-.6663	-.5722	0.1159	-.1294
R34	0.4665	0.5353	0.5598	0.6525	0.2116
R12	0.5792	0.6995	0.7605	0.4196	0.2945
R38	0.7469	0.8409	0.8778	0.5252	0.3035
R8	0.9841	0.9254	0.8490	0.3900	0.2630
R16	1.0000	0.9710	0.9127	0.4138	0.2472
R30	0.9710	1.0000	0.9761	0.4946	0.2420
R50	0.9127	0.9761	1.0000	0.5384	0.2328
R200	0.4138	0.4946	0.5384	1.0000	0.2641
SE	0.6530	0.7805	0.8212	0.5454	0.2150
FAA	-.0581	-.2005	-.2777	-.7576	-.1146
CAA	-.3277	-.2218	-.1387	-.5007	-.1536
DP	-.2995	-.3778	-.4224	-.9410	-.2170

	SE	FAA	CAA	DP
VA	0.3088	0.0652	-.1785	-.1484
VMA	0.0185	-.0427	-.1051	-.0959
DENSITY	0.4079	-.4020	-.4443	-.5248
PB	-.4530	0.5302	0.4733	0.5090
NMAX	-.1745	0.1546	0.3046	0.1743
NMIN	-.2541	-.4970	0.0068	-.2159
R34	0.5501	-.5692	-.3762	-.5521
R12	0.7586	-.3070	0.2134	-.2938
R38	0.8029	-.3462	0.0173	-.3964
R8	0.5655	-.0009	-.4005	-.2757
R16	0.6530	-.0581	-.3277	-.2995
R30	0.7805	-.2005	-.2218	-.3778
R50	0.8212	-.2777	-.1387	-.4224
R200	0.5454	-.7576	-.5007	-.9410
SE	1.0000	-.4922	0.0027	-.4725
FAA	-.4922	1.0000	0.3182	0.7265
CAA	0.0027	0.3182	1.0000	0.4541
DP	-.4725	0.7265	0.4541	1.0000

Eigenvalues of the Correlation Matrix

	Eigenvalue	Difference	Proportion	Cumulative
PRIN1	8.57812	5.36693	0.451480	0.45148
PRIN2	3.21119	1.31727	0.169010	0.62049
PRIN3	1.89391	0.77932	0.099680	0.72017
PRIN4	1.11459	0.14694	0.058663	0.77883
PRIN5	0.96765	0.02143	0.050929	0.82976
PRIN6	0.94622	0.38591	0.049801	0.87956
PRIN7	0.56031	0.08725	0.029490	0.90905
PRIN8	0.47306	0.10574	0.024898	0.93395
PRIN9	0.36732	0.03378	0.019333	0.95328
PRIN10	0.33354	0.11683	0.017555	0.97084
PRIN11	0.21671	0.08195	0.011406	0.98224
PRIN12	0.13476	0.04705	0.007093	0.98934
PRIN13	0.08771	0.04157	0.004616	0.99395
PRIN14	0.04614	0.01845	0.002429	0.99638
PRIN15	0.02769	0.00575	0.001457	0.99784
PRIN16	0.02194	0.01058	0.001155	0.99899
PRIN17	0.01136	0.00548	0.000598	0.99959
PRIN18	0.00588	0.00401	0.000310	0.99990
PRIN19	0.00188	.	0.000099	1.00000

APPENDIX B: MC Output for Va of SM-2C (Let)

Dependent Var. : 1 VA

Sy.x = 0.18311 RSQ = 0.9414 Deg Freedom = 95

VARIABLES IN THE EQUATION

Var	Coefficient	T	RSQ	LABEL
0	-7.34704405E+01			Intercept
4	-2.78508467E-01	-1.93	0.70	PB
5	8.45505365E+00	8.60	1.00	GMMMAX
6	-8.65831560E+00	-8.13	1.00	GMMMIN
8	-1.92208202E-03	-0.21	0.91	R12
12	2.55789953E+00	1.87	1.00	R30
16	-8.35160626E-01	-1.74	1.00	SE
21	8.32486979E-02	5.43	1.00	GMMMIN*R30
27	-9.96487703E-02	-8.68	1.00	R30*GMMMAX
31	9.59480444E-03	1.73	1.00	SE*GMMMIN

VARIABLES NOT IN THE EQUATION

VAR	22	23	24	25	26	28	29
T	1.44	-1.09	1.94	1.45	-2.26	0.96	-1.93
RSQ	1.00	1.00	1.00	1.00	1.00	1.00	1.00

VAR	30	32	33	34	35
T	1.48	0.17	0.09	-0.57	-0.84
RSQ	1.00	1.00	1.00	1.00	1.00

ROWS DELETED : None